Fintech and Racial Barriers in Small Business Lending

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Abstract

Why are fintech lenders more popular among minority-owned businesses? We provide novel evidence on this question using a linked database on a national-wide restaurant sample from Yelp and Paycheck Protection Program (PPP) loans. We show that in a simple two-sided matching model, three distinct channels can lead to a higher fintech usage by minority borrowers: 1) differences in operational performance between minority and non-minority borrowers; 2) a smaller proportion of minority borrowers having lending relationships; 3) racial-dependent factors affecting the value of the borrower-lender matches. Empirically, we do not find consistent evidence on the first channel. We find supporting evidence for the second channel that minority-owned restaurants are less likely to have lending relationships and restaurants without lending relationships are more likely to use fintech lenders. We also find evidence supporting the third channel that minority-owned restaurants are more undervalued by traditional than fintech lenders. We further show that higher levels of business capital on the borrower side and a smaller geographic scope on the lender side can mitigate the racial gap in the value of the borrower-lender match. The results in 2021 become statistically insignificant, suggesting that racial disparities are largely reduced. We do not find a similar pattern for first-time bank participants, community development financial institutions, credit unions, or other non-federally insured lenders. Minority-owned businesses preferring faster loan approval also cannot explain the racial disparities we document. Overall, our results suggest that there are racial barriers in traditional loan distribution channels that can be at least partially addressed by fintech lenders.

Keywords: Racial Barriers, Minority-owned Businesses, Paycheck Protection Program, Small Business Lending, Bank Lending, Nonbank Lending, Fintech.

JEL No. D63, G2, G21, G28, H25, M14

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1. Introduction

It has been long documented that minority-owned businesses are less likely to access the traditional credit market (Bates, 1997; Tareque et. al., 2021).[1] More recent evidence shows that fintech companies and online banks are being used more among minority-owned businesses (SBCS, 2021), even when the government removes all credit risk from lenders (Erel and Liebersohn, 2020). However, empirical studies are scarce on whether this is due to economic barriers or statistical discrimination (Becker, 1957; Arrow, 1971; Phelps, 1972), probably due to the lack of data on small business lending.

In this paper, we attempt to fill the gap by providing novel evidence on the following question: are fintech lenders more popular among minority-owned businesses simply because of differences in their operational performance per se, or because minority-owned businesses are less valued at traditional lenders? As fintech lending largely reduces in-person interactions, limiting opportunities for racial barriers, it is plausible that minority borrowers would prefer fintech because fintech lenders provide more value to them.

We answer this question by exploiting the unique design of the Paycheck Protection Program (PPP), a key component of the Coronavirus Aid, Relief, and Economic Security (CARES) Act that began on April 3, 2020.[2] It provides a nice laboratory to study the question for several reasons. First, the loan terms are fixed by the SBA, which rules out that fintech lenders attract different borrowers because of more flexible loan terms. Second, all small businesses are hit by the Covid-19 shock almost simultaneously, and applications start on the same day for all borrowers. This controls for the impact of the business development stage on fintech usage. Third, the entry of fintech lenders is largely driven by the sudden demand for loan processing in the pandemic. This mitigates supply-side endogeneity concerns as fintech lenders target a specific segment of minority borrowers. Fourth, as discussed in several papers (Amiram, and Rabetti, 2020; Balyuk, Prabhala, and Puri, 2020; Duchin et. al., 2021), the credit risk concern in the PPP is fully transferred to the

[1] Other papers include Cavalluzo and Cavalluzo (1998), Cavalluzzo, Cavalluzzo, and Wolken (2002), Blanchflower, Levine, and Zimmerman (2003), Cavalluzzo and Wolken (2005), Blanchard, Zhao, and Yinger (2008), Asiedu, Freeman, and Nti-Addae (2012), and Bates and Robb (2013, 2015). Additionally, Cherry et. al. (2021) find that borrowers in minority-dominated regions were more likely to obtain debt relief during the Covid-19 pandemic.

[2] More information on the PPP program is provided in the Appendix. Also, see https://www.sba.gov/funding-programs/loans/covid-19-relief-options/paycheck-protection-program

government. Thus, differences in the use of fintech lenders by minority and non-minority borrowers cannot be explained by the risk management of lenders.

In addition, the PPP provides a unique dataset that covers the segment of borrowers that, under normal circumstances, are impeded by high barriers to accessing the credit market and thus do not appear in conventional loan application datasets. However, since the Covid-19 crisis is an economy-wide shock, the high demand for credit, plus the extremely low interest rate and the possibility of forgiveness, provides strong incentives for any borrower to participate.[3]

We start by documenting racial disparities in the PPP, using our national-wide sample of over 98,000 Yelp restaurants linked to first-draw recipients in 2020 and 2021.[4] The results are consistent with the existing literature. Figure 1 shows that in 2021, non-fintech lenders deliver more loans to non-minority-owned businesses (Figure 1(a)). In contrast, there is no such a clear minority-non-minority gap for fintech lenders (Figure 1(b)). In our regression analysis, we also find a positive relationship between fintech usage and being minority-owned businesses. Interestingly, taking Asians in 2020 as an example, while the magnitude of positive relationship decreases by 20% after controlling for city fixed effects, which suggests that the geographic variation across cities explains a large part of the variation in fintech usage.

Next, we develop a simple two-sided matching game model to understand the mechanisms leading to this phenomenon. First, even in equilibrium without racial disparities in the lending market, our model predicts that more minority-owned businesses using fintech lenders can be generated by a positive (negative) correlation between operational performance and fintech usage,[5] combined with minority-owned businesses have better (worse) operational performance. Second, the existing literature shows that the crowding-out effect of lending relationships is pronounced in the PPP (Li and Strahan, forthcoming; Amiram, and Rabetti, 2020; Duchin et. al., 2021). Given the crowding-out effect, our model predicts that, even in equilibrium where the *value* of borrower-lender matches are race-independent, if fewer minority-owned businesses had bank lending relationships in the pre-Covid period, more of them would be crowded out of the traditional credit

[3] Admittedly, some borrowers might be rejected after the loan application, but the survey results in Bartik et. al. (2021) suggest that inability to submit an application accounts for two-thirds of the loan denials and in total only 8% of the loan applications are rejected by the SBA.
[4] The first draw refers to first-time loans applied by borrowers in 2020 and 2021. The second draw refers to the re-application of a second loan in 2021.
[5] Even in a fully government-guaranteed loan program, fintech usage can correlate with the borrower's operational performance due to businesses of better operational performance self-selecting into fintech lenders or lower performance borrowers who have bank lending relationships crowding out other borrowers to fintech lenders.

market and turn to fintech lenders instead. Third, in race-dependent equilibrium, our model also predicts a higher fintech usage for minority-owned businesses, even without a difference in operational performance or the proportion of borrowers having lending relationships. In reality, the *value* of technology or lending relationships can be different for minority and non-minority borrowers, leading to racial barriers in the lending market.

One distinct feature of the third case is that we observe a difference in the minority-non-minority operational performance gap between those using fintech and non-fintech lenders (i.e. a double difference in the operational performance). This prediction does not hold in the first two cases. Empirically, based on this insight, if we find evidence of a more negative minority-non-minority operational performance gap for fintech lenders, this implies that traditional lenders have a lower value for minority-owned businesses than fintech lenders.

It is important to distinguish between these explanations because they have different policy implications for racial disparities in small business lending. The first explanation does not imply racial disparities in the lending market. In contrast, the second and third explanations call for greater attention to equitable credit access for small businesses owners, whether in terms of alleviating the negative effect of lending relationships or reducing barriers in the lending procedure.

Our empirical analyses focus on PPP recipients in the *Food Services and Drinking Places* sector for which we can find a Yelp webpage.[6] While restaurants only account for 4.40% of PPP loans, it offers several critical advantages for our study. First, it allows us to address the limitation of the PPP loan-level data that it misses the race and ethnicity of recipients for almost 80% of the sample. We build a proxy for minority-owned businesses based on the food type information on yelp.com.[7] In addition, we obtain data on customer ratings, a proxy for operational performance. Second, almost all restaurants are eligible for the PPP program and therefore there is no additional variation resulting from regulation.[8] Third, restaurants are among the most Covid-vulnerable sectors (Fairlie, 2020; Buffington et. al., 2021; Fairlie and Fossen, 2021b)[9], which provides strong

[6] To have a comparable sample, we focus on yelp webpages of restaurants. Others are gyms, nail bars, hotels, etc.
[7] Overall, as we present in detail, our racial group measures have reasonable accuracy when compared with the racial and ethnic information reported in the PPP data for the 20% of the sample of non-missing values.
[8] For most industries, the eligibility requirement is either meeting the SBA size standards for small businesses or less than 500 employees. For the industries with a NAICS code that begins with 72 (Accommodations and Food Services), the business is eligible for the PPP as long as the number of employees is fewer than 500 at each location.
[9] Other papers having the same findings or classifications include Alekseev et. al. (2021), Balyuk, Prabhala, and Puri (2020), Berger et. al. (2021), and Fazio et. al. (2021).

incentives for borrowers to participate in the PPP. For the classifications of lenders, we mainly rely on the *FinTech Company List* published by the SBA, with manual checks of all non-banks.

Importantly, while we view the national-wide geographic scope and direct measurement of minority ownership on a firm-by-firm basis as strengths of our data construction, we acknowledge the incompleteness of sample coverage and the non-100% accuracy of the minority measurement.[10] By focusing on a subsample of PPP loans, our analyses aim to provide evidence of racial disparities and barriers in small business lending and the role of fintech lenders in alleviating them rather than assessing the efficacy of the PPP.

In the empirical analyses, we do not find consistent evidence on the first channel. While we do find evidence that is consistent with the self-selection or the crowding-out effect for fintech usage, the overall difference in ratings is insignificant or lower for minority-owned businesses. This would yield that minority-owned businesses are indifferent or less likely to use fintech lenders. Therefore, the higher popularity of fintech lenders among minority-owned businesses is unlikely to be attributed to a rating difference between minority and non-minority-owned businesses.

Instead, we find evidence supporting the second and third channels. Regarding the second channel, we find two pieces of evidence that, if combined, can lead to higher usage of fintech lenders among minority-owned businesses. First, we find that among the 2020 PPP recipients, minority-owned businesses are less likely to have lending relationships, and if they do, it is less intensive. Interestingly, racial disparities in lending relationships no longer exist among the 2021 PPP recipients. Second, our evidence shows that borrowers with no or few lending relationships are more likely to gain a PPP loan through fintech lenders.

Our findings also support the third channel. We document that the difference between minority- and non-minority-owned restaurants in customer ratings is more negative for fintech lenders. According to our model, this suggests that minority-owned restaurants have a higher valuation when matched with fintech than traditional lenders.[11] The intuition behind this is that if fintech lenders have a higher valuation of minority borrowers than traditional lenders, they demand a lower bar for minority borrowers. In other words, minority-owned restaurants face lower barriers when using fintech lenders. The results are consistent when restricting to a matched sample using

[10] Our minority measure is most accurate for Asian-owned restaurants and all the results in 2020 are statistically significant at 1% for Asian-owned restaurants as well.

[11] We would not observe a more negative difference between minority- and non-minority-owned restaurants in ratings if more minority-owned small businesses use fintech lenders only due to the lack of previous lending relationships.

business locations, food price range, and other characteristics as matching covariates. Furthermore, the results are robust when controlling for city times month fixed effects. Moreover, the magnitude of the difference in ratings can be used as a proxy for the level of racial barriers. Comparing the results for the 2020 and 2021 waves, we also observe a reduction in racial barriers in 2021.

When exploring heterogeneity among lenders, we find that the four largest banks in our sample, JPMorgan, Bank of America, Wells Fargo, U.S. Bank, do not have a large minority-non-minority rating gap. The rating gap is more pronounced for relatively "small" big banks, Truist, PNC, and TD Bank, implying that smaller banks have higher racial barriers in the lending procedure. Our evidence is consistent with the findings in Howell et. al. (2021) that "smaller banks were much less likely to lend to Black-owned firms, while the Top-4 banks exhibited little to no disparity."

Furthermore, we investigate sources of racial barriers by exploring factors affecting the level of barriers. We find that the difference between fintech and traditional lenders in the minority-non-minority rating gap is smaller if borrowers have higher levels of business capital, proxied by the monthly number of ratings. For instance, for Asian recipients in 2020, one standard deviation increase in business capital reduces the minority-non-minority rating gap in the benchmark case by 106.69%. Business capital can be seen as soft assets that can mitigate racial barriers in the lending procedure. As a result, the value of technology is lower for minority borrowers with higher levels of business capital. In this sense, our evidence is consistent with a different value of technology for minority and non-minority borrowers being one source of racial barriers.

On the lender side, we find evidence that the difference in the minority-non-minority rating gap is smaller for more geographically focused lenders. Existing literature suggests that more geographically focused lenders tend to have more valuable lending relationships (Agarwal and Hauswald, 2010). Therefore, our finding indicates that a lower *value* of lending relationships for minority borrowers is another source of racial barriers.

We rule out several non-technology-related features of fintech lenders by studying other lender classifications. We do not find a similar pattern in lender usage and rating gaps for the first-time banks (banks that did not previously participate in SBA 7(a) and 504 programs), community development financial institutions and corporations, credit unions, non-federally insured lenders, or savings & loan associations. We also rule out the possibility that minority-owned businesses are more likely to choose fintech lenders because of quicker approval. We find that, if anything, minority-owned businesses in 2020 who applied through fintech lenders waited longer to have a loan approved. Moreover, our results on the minority-non-minority rating gap are robust when controlling for approval date fixed effects, meaning that the racial gap does not come from a difference in loans approved earlier or later.

Overall, our findings suggest that there exist racial barriers and blind spots in the traditional small business lending market. In the PPP program, minority-owned businesses are more likely to use fintech lenders. More importantly, we show that this effect cannot be simply explained by a performance difference between minority- and non-minority-owned businesses. There are deep-rooted racial disparities in terms of who has lending relationships, benefits from a lending procedure featuring fewer human-to-human contacts, and the value of lending relationships. On the bright side, consistent with the existing literature (Chernenko and Scharfstein, 2021; Fairlie and Fossen, 2021c), our evidence suggests that the racial gap is largely reduced in 2021, potentially due to the efforts of the Biden Administration.

There is a large body of literature on the PPP program.[12] In particular, several papers look at racial disparities in the program. Studies using the early release of the PPP loan-level dataset conduct county/zip code-level analysis (Fairlie and Fossen, 2021a; Erel and Liebersohn (2020); Wang and Zhang, 2020) or use the subsample having race and ethnicity information (Atkins, Cook, and Seamans, 2021). Two contemporaneous papers, Chernenko and Scharfstein (2021) and Howell et. al. (2021), like our paper, also link the PPP dataset with other data sources to create a firm-level minority measure that allows for a richer set of findings.

Notably, our sample differs from theirs. Chernenko and Scharfstein (2021) use restaurant registry data in the state of Florida to determine the racial and ethnic group of the owner, which has a high degree of accuracy. That said, our dataset covers all states and provides information on restaurant operational performance both before and during the Covid-19 crisis. Howell et. al. (2021) use a machine-learning algorithm to predict the business owner's racial group that uses the owner's name, the firm's location, and other information. In contrast, our measure is more direct and thus

[12] See Berger and Demirgüç-Kunt (2021) for an early survey. Examples include Bartik et. al. (2020) and Granja et. al. (2020) on accessing the allocation, Autor et. al. (2020) on sustaining employment, Balyuk, Prabhala, and Puri (2020) and Cororaton and Rosen (2020) on reputational and disruption costs of receiving the PPP funds, Duchin et. al. (2021) on favoritism of lending relationships, Humphries, Neilson, and Ulyssea (2020) on information frictions in the loan application procedure, Bartlett and Morse (forthcoming), Berger et. al. (2021), Denes, Lagaras and Tsoutsoura (2021) on real effects of the program, Berger, Karakaplan, and Roman (2021) and Duchin and Hackney (forthcoming) on political influence on the fund allocation.

allows us to control for location and business type variables in empirical analyses without concerns on the double usage of the same information. Acknowledging the data richness in Howell et. al. (2021) that relies on several proprietary datasets, our study provides sufficient economic insights using publicly available data sources.

Our paper contributes to the literature on racial disparities in the PPP in several ways. First, we provide novel evidence to the scant literature on this important topic. Using a different sample and a different research design, our evidence is largely consistent with the two seminal contemporaneous papers Chernenko and Scharfstein (2021) and Howell et. al. (2021) and provides further supports for the existence of racial disparities in the PPP. Second, we look at racial disparities through the lens of real-economy performance measures, which, to our best knowledge, is not investigated in other papers. From the view of society, it is important to know whether the traditional credit market serves a different segment of minority- versus non-minority-owned businesses than fintech lenders in terms of real-economy performance. Third, our evidence highlights an under-investigated but important type of racial disparities on the borrower side: barriers to reaching out to the same lender can be higher for minority borrowers. This supplements the finding in Howell et. al. (2021) that the nature of the lending process is a key factor in explaining the higher usage of fintech lenders by minority borrowers. A more automatic lending process also lowers the level of barriers to a larger degree for minority borrowers.[13]

Our paper is also related to the nascent literature on fintech lending, particularly on the financial inclusion role of fintech lenders (Jagtiani and Lemieux, 2018; Mills and McCarthy, 2016), the relationship with traditional lenders in small business lending (Cumming et. al., 2019; Gopal and Schnabl, 2020; Beaumont, Tang, and Vansteenbergh, 2021), borrower side factors affecting fintech usage such as misreporting (Griffin, Kruger and Mahajan, 2021) and trust in the banking system (Yang, 2021), and racial discrimination in the lending procedure (Bartlett et. al., 2021; Fuster et. al., forthcoming; D'Acunto et. al., 2020). Our paper adds to the literature by showing that one role of fintech lenders on achieving a more equitable lending market is to provide credits to minority borrowers who are facing higher barriers and undervalued at traditional lenders.

[13] In addition, in Howell et. al. (2021), they conclude that lending relationships play a tiny role in explaining racial disparities in fintech usage because coefficients change little after adding a control variable for lending relationships. In contrast, our model and empirical evidence show two economic channels on how lending relationships affect fintech usage: 1) the crowding-out effect of borrowers with lending relationships plus a weaker lending relationship in the pre-Covid period for minority borrowers; 2) the value of lending relationships is lower for minority borrowers.

The paper proceeds as follows. Section 2 presents a simple matching game model. Section 3 describes the data sources, the sample, and provides summary statistics. Section 4 provides evidence on the existence of racial disparities in borrower-lender matching. Section 5 shows the evidence on different channels generating racial disparities. Section 6 discusses alternative explanations. Section 7 concludes.

2. A Simple Model of The Borrower-Lender Matching Game

In this section, we develop a simple transferable utility matching game model (Azevedo and Hatfield 2018) to illustrate the matching process between borrowers and lenders in the PPP program. We present the basic model setup and the main results here. Further details on the assumptions, formal mathematical presentations and detailed deviations, and discussions can be found in the Online Appendix D.

Model Setup. There are a group of minority borrowers with a mass of M^m and a group of non-minority borrowers with a mass of M^n whose ratings follow the normal distribution $\gamma_i^m \sim N(\mu^m, \sigma^m)$, and $\gamma_i^n \sim N(\mu^n, \sigma^n)$ respectively.[14] There are a group of fintech lenders with a mass of M^f and a group of banks with a mass of M^b.

Payoff Function. The payoff function of a match between the borrower i and the lender j, $p_{i,j}(\gamma_i, \theta_{i,j})$, depends on the borrower's rating level γ_i and a lender-borrower dependent factor $\theta_{i,j}$, such as the borrower's preference for technology and the value of previous lending relationships between the borrower and the lender. $\theta_{i,j}$ is racial-neutral when we study the scenario with no taste-based discriminations. We study the equilibrium under taste-based discriminations using $\theta_{i,j}$ = $\theta_{i,j}^m$ for minorities and $\theta_{i,j}$ = $\theta_{i,j}^n$ for non-minorities. For simplification purposes, we assume that the payoff function is increasing in the borrower's rating γ_i and is of a linear functional form $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta_{i,j}$.

Matching Game. Without loss of generality, we study a 1-lender-m-borrower matching game.[15] The borrower i chooses a lender to apply to with an offered transferred utility (price). If

[14] Empirical patterns in Figure 2 support a normal distribution of ratings.
[15] In the PPP program, observations where a borrower is granted multiple loans are few. In our sample construction, fewer than 2% of the restaurants appeared to be associated with multiple loans. We exclude those observations from our analysis sample.

the lender *j* accepts the application from the borrower i, a match (i,j) happens and the lender gains the transferred utility and the borrower gains the total payoff $p_{i,j}(\gamma_i, \theta_{i,j})$ minus the transferred utility. If the lender *j* rejects the application from the borrower i, no match between the borrower *i* and the lender *j* happens and no total payoff is generated. The borrower *i* may apply to another lender or renegotiate the offered transferred utility. If no lender is willing to accept the borrower for any transferred utility that leaves a non-negative payoff to the borrower, the borrower is unmatched.

Equilibrium. In a competitive equilibrium, incentive compatibility means any deviation from either the borrower side or the lender side cannot achieve a higher payoff. The prices (transferred utilities) clear the market such that

$$p_{i,j}(\gamma_i, \theta_{i,j}) \geq p_{i,j'}(\gamma_i, \theta_{i,j'})\ for\ j' \neq j \text{ and } p_{i,j}(\gamma_i, \theta_{i,j}) \geq p_{i',j}(\gamma_{i'}, \theta_{i',j})\ for\ i' \in I \backslash I_j^* \quad (1)$$

Where *I* is the entire borrower set, and I_j^* is the optimal choice set of lender j.

In the following paragraphs, we discuss three scenarios. In the first scenario, the payoff function only depends on the rating level of the borrower. In the second scenario, the payoff function depends on the rating level of the borrower as well as a race-neutral lender-borrower factor $\theta_{i,j}$. In the third scenario, the payoff function depends on the rating level of the borrower and a race-biased lender-borrower factor $\theta_{i,j}^{m/n}$.

Scenario 1 – Benchmark. We first study the benchmark case where the payoff function only depends on the borrower's rating level $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i$. We have a unique symmetric equilibrium where fintech lenders and banks are matched with borrowers whose ratings are above the same threshold $\underline{\gamma}$ for both the minority and non-minority groups. $\underline{\gamma}$ is determined by

$$\delta M^m \int_{\underline{\gamma}}^{\infty} f(x, \mu^m, \sigma^m) dx + \delta M^n \int_{\underline{\gamma}}^{\infty} f(x, \mu^n, \sigma^n) dx = M^f$$

$$(1-\delta) M^m \int_{\underline{\gamma}}^{\infty} f(x, \mu^m, \sigma^m) dx + (1-\delta) M^n \int_{\underline{\gamma}}^{\infty} f(x, \mu^n, \sigma^n) dx = M^b$$

Where $f(\mu^m, \sigma^m)$ and $f(\mu^n, \sigma^n)$ are the density functions of the rating distribution for the minority and non-minority borrowers respectively.

[INSERT FIGURE 2 AROUND HERE]

One thing to notice is that even in this case where the payoff function is not borrower-lender specific, the percentage of matched borrowers, i.e. those who obtain a loan, can vary across racial groups if the rating distributions are different. Figure 2 shows that, in our sample, the rating distributions of Asian- and Hispanic-owned restaurants appear to have the same mean as non-minority-owned restaurants while African American-owned ones have a larger mean.[16] In equilibrium, a higher (lower) mean of the rating distribution results in a higher (lower) percentage of matched borrowers, which is aligned with statistical discrimination.

Scenario 2 – Race-Neutral Borrower-Lender-Specific Payoff. In the second scenario, the payoff function depends on the rating of the borrower as well as a *race-neutral* borrower-lender-specific factor $\theta_{i,j}$. We consider two reasons why the payoff function can be borrower-lender specific.

First, we consider the tech-preference case and assume that higher-rated borrowers have a higher preference for technology and therefore have a higher payoff when matched with fintech lenders than with banks.[17] Notably, however, we assume that minority and non-minority borrowers of the same rating level have the same additional preference for fintech lenders to banks. In this case, we still have a race-neutral equilibrium in terms of rating levels of minority and non-minority borrowers matched with fintech lenders and with banks. Unlike the benchmark case, the average rating of borrowers matched with fintech lenders is higher than banks due to the self-selection of higher-rated borrowers into fintech lenders.

Second, we discuss the lending-relationship case where the payoff functions are different for borrower-bank matches with and without previous lending relationships but in a race-neutral way. Previous lending relationships play a crucial role in the PPP program (Li and Strahan forthcoming; Duchin et. al. 2021). For example, on the lender side, helping existing customers to survive the crisis may alleviate the debt overhang problem (Amiram and Rabetti 2020). On the borrower side, the existing profile of the borrower can make it easier to navigate the application process.

In this case, we also have a race-neutral equilibrium in terms of rating levels. Because of the additional utility from lending relationships, the marginal borrower with lending relationships is

[16] We also present regression results in Online Appendix B Table B2 showing that African Americans have higher ratings and Asians and Hispanics have lower ratings on average, controlling for other characteristics.

[17] We have similar results if assuming lower-rated borrowers have a higher preference for technology. Detailed discussions in Online Appendix D. Since our empirical pattern is consistent with that higher-rated borrowers self-select into fintech lenders, we make the assumption in the increasing direction in the main text.

of a lower rating level than the marginal borrower without lending relationships. This crowds out some of the higher-rated borrowers without lending relationships from banks to fintech lenders, which results in a higher average rating level for borrowers matched with fintech lenders than with banks.

In our model, the phenomenon that minority borrowers being more likely to be matched with fintech lenders can occur even if the payoff function is race-neutral. Firstly, it can be generated through the channel of higher average ratings for minority borrowers, combined with the self-selection effect of higher-rated borrowers or the crowding-out effect by lower-rated borrowers having bank lending relationships. Additionally, it can also be attributed to a smaller mass of minority borrowers having lending relationships than non-minority borrowers.

Scenario 3 – Race-Biased Borrower-Lender-Specific Payoff. In the third scenario, the payoff function depends on the rating of the borrower as well as a *race-biased* borrower-lender-specific factor $\theta_{i,j}^{m/n}$. There can be several reasons for such a difference in the payoff for fintech lenders versus banks between the minority and non-minority borrowers. For example, a less bureaucratic process and fewer human contacts in a fintech loan application may benefit minority borrowers who may have language and culture barriers. It is also possible that minority borrowers might have had previous negative experiences with banks and therefore have a higher expectation from new technology-oriented lenders. On the lender side, it is much less costly for fintech lenders to reach any region, including those that are covered less by traditional financial institutions but with a larger minority population.

First, we study the tech-preference case where the additional utility gain from matching with fintech lenders is race-biased. As in the race-neutral case, the additional utility from technology results in a higher matching threshold in terms of rating levels for fintech lenders than for banks. Unlike the race-neutral case, the equilibrium is race-asymmetric in terms of the matching thresholds in ratings for fintech lenders. For the group of borrowers that have a higher value for fintech lenders, they are willing to transfer a higher share of the total payoff to fintech lenders. This results in a smaller matching threshold of fintech lenders for that group of borrowers. Proposition 1 presents this result.

Proposition 1

In the race-biased tech-preference case, the matching thresholds for the matches of minority-fintech, non-minority-fintech, minority-bank, and non-minority-bank in equilibrium satisfy,

$$\underline{\gamma_{mf}} = \frac{\theta^n}{\theta^m}\underline{\gamma_{nf}}$$

$$\underline{\gamma_{mb}} = \underline{\gamma_{nb}}$$

■

Proof in the Appendix.

Proposition 1 implies that when minority borrowers have a higher preference for technology than non-minority borrowers with the same rating level ($\theta^m > \theta^n$), the matching threshold with fintech lenders is lower for minority borrowers than for non-minority borrowers ($\underline{\gamma_{mf}} < \underline{\gamma_{nf}}$). This has two important implications. First, a lower matching threshold for minority-fintech matches results in a relatively larger share of minority borrowers than non-minority borrowers using fintech lenders even without a difference in the underlying rating distribution. Second, a lower matching threshold for minority-fintech matches implies a more negative minority-non-minority rating gap of the marginal borrower for fintech lenders, which can be translated into a more negative minority-non-minority rating gap in the expected mean of matched pairs for fintech lenders. Corollary 1 presents this result.

Corollary 1

The minority-non-minority rating gap in the matching thresholds is more *negative* (*positive*) for fintech lenders when minority borrowers compared with non-minority borrowers have a *higher* (*lower*) value of matches with fintech lenders.

$$\left(\underline{\gamma_{mf}} - \underline{\gamma_{nf}}\right) - \left(\underline{\gamma_{mb}} - \underline{\gamma_{nb}}\right) \lesseqgtr 0 \ if \ \theta^m \gtreqless \theta^n$$

Suppose that the underlying distribution is the same for minority and non-minority borrowers, i.e., $\mu^m = \mu^n = \mu$ and $\sigma^m = \sigma^n = \sigma$, then the minority-non-minority rating gap between fintech lenders and banks in the conditional expectation of the rating levels equals $\sigma\left(G\left(\frac{\underline{\gamma_{mf}}-\mu}{\sigma}\right) -\right.$

$G\left(\frac{\gamma_{nf}-\mu}{\sigma}\right)\Bigg)$, where $G(x) = \frac{\varphi(x)}{\Phi(-x)} + \frac{\varphi(x)-\varphi(\tilde{\gamma})}{\Phi(x)-\Phi(\tilde{\gamma})}$, with $\tilde{\gamma} = \frac{\gamma_{mb}-\mu}{\sigma}$ and $\varphi(\cdot)$ and $\Phi(\cdot)$ as the density and cumulative distribution functions of the standard normal distribution respectively.

■

Proof in the Appendix.

Second, we study the lending-relationship case where the payoff function contains an additional utility gain for borrower-lender matches with previous lending relationships which is race-biased. Mirroring the tech-preference case, the equilibrium is race-asymmetric in matching thresholds for borrowers with previous lending relationships. This is because the racial group of borrowers with a higher value of lending relationships are willing to transfer a higher share of the total payoff to lenders. As a result, the matching threshold in equilibrium is smaller for that racial group. For borrowers without lending relationships, the matching threshold in equilibrium is race-independent because their outside option is the same. Similar to the tech-preference case, the race-asymmetric matching thresholds further translate into a racial gap in the shares as well as the average rating levels of borrowers that are matched with fintech lenders and banks.

In summary, our model shows that the phenomenon that a higher usage rate of fintech lenders among minority borrowers can be generated through several distinct channels. On the one hand, it can exist in a race-neutral equilibrium through two channels. First, the combination of higher- (lower-) rated borrowers being more likely to be matched with fintech lenders, whether due to the self-selection or the crowding-out effects, and a higher- (lower-) average rating for minority-owned businesses can be one channel. Second, if fewer minority borrowers have lending relationships with banks, we also observe more fintech usage among minority borrowers than among non-minority borrowers. On the other hand, racial bias can also lead to the difference in the usage of fintech and non-fintech lenders. In our model, we show that if minority borrowers have a higher preference for technology-based lending process or if the value of lending relationships is higher for non-minority borrowers, a larger share of minority borrowers are matched with fintech lenders in equilibrium. Notably, we also observe a difference in the minority-non-minority rating gap between fintech and non-fintech lenders in the race-biased case. We shall test the different channels in the empirical analysis followed.

3. Data and Summary Statistics

3.1. Data sources

Our analysis relies mainly on a linked database of loan-level information on restaurants in the Paycheck Protection Program (PPP) and the full history of customer ratings downloaded from Yelp.com. For the PPP dataset, we use the loan-level data release on March 2, 2021 (through sba.gov, FOIA), which is the most detailed and comprehensive version of loans of all sizes. The entire PPP dataset contains around 6.46 million loans processed by 5,593 lenders, among which around 0.37 million loans (5.77%) are for businesses in the *Food Services and Drinking Places* sector (NAICS code 722). The key information we use from the PPP data includes the business name, address, state, zip code, industry, business entity type, reported employment size, and franchise name for borrowers; and the formal organization name, address, city, state, and zip code for lenders. We restrict our loan sample to only first draws in order to better capture the matching between borrowers and lenders. The completeness of the 2021-March release of the PPP data enables us to address questions that have not been answered in previous studies,[18] and is crucial for our study because minority-led businesses tend to be smaller (Fairlie and Robb 2008; U.S. Census Bureau 2016; Tareque et. al. 2021) and received a smaller loan (Atkins, Cook, and Seamans 2021; Fairlie and Fossen 2021a).

First and foremost, to carry out our analysis we need to distinguish between traditional and fintech lenders, for which we mainly rely on the *FinTech Company List* published on the SBA official website (sba.gov). We supplement the official *FinTech Company List* with information from the SBA state subsidiaries' websites and major news sources.[19] We identify 15 fintech lenders and the full list is in Table A2 in the Appendix.[20] Examples of fintech lenders in our list are Kabbage, Square, and Paypal. Appendix-Table A2 also reports the percentage of loans that are included in our final sample linked with Yelp ratings, which indicates that our linked sample is evenly distributed across each fintech lender. We present the comparison between our sample and

[18] Other papers studying the Paycheck Protection Program (Erel and Liebersohn 2020; Granja et. al. 2020; Li and Strahan forthcoming) use the early release of the PPP data that contains borrower names only for loans *above* $150,000. The full release used in our paper contains borrower-level identifiable information for loans both above and below $150,000, which enables us to link with Yelp rating data for the full sample.

[19] To cross validate our consolidated fintech company list, we manually go through the entire sample of non-bank lenders and do not identify any lenders that are clearly a fintech company but not in our fintech lender list.

[20] The 2020-March data release includes both the originating and the servicing lenders, and we classify the pair of lenders as a fintech lender when either of them is in our consolidated list of fintech lenders.

the Erel and Liebersohn (2020) sample in the Online Appendix B-Table B1, which further confirms the reliability of our classification. Details on the construction of the sample of fintech lenders are stated in the Online Appendix C1.

One thing to notice about our classification method is that we do not classify all non-banks as fintech lenders because one crucial feature of SBA lending programs is the participation of many traditional non-bank lenders, such as CRF Small Business Loan Company, LLC and Hana Small Business Lending, Inc., as means to facilitate the funding needs of less bank-connected small businesses. Regarding the lending technology, these non-banks are similar to banks and are different from fintech companies. Other papers on small business lending (Gopal and Schnabl 2020) and the mortgage credit market (Buchak et. al. 2018; Fuster et. al. 2019) also make the distinction between fintech companies and other non-banks.

Second, we need to identify minority-owned businesses among PPP loan recipients for a representative sample. One limitation of the PPP loan-level data is that the information on the race and ethnicity of loan recipients is missing for almost 80% of the sample.[21] Because there might be a selection bias in the sample that has the demographic information, we do not rely on the demographic information in the original PPP loan-level dataset. To address this challenge, we restrict to a sample of restaurants among the PPP recipients for which we find a match on yelp.com. Then we use the food type information on yelp.com as a proxy for the race and ethnicity information of the restaurant owners. We classify restaurants into four groups: African American, Asian (including Pacific Islander), Hispanic, and White. The detailed classification list is available upon request.[22] We cross validate our measure of minority-owned business by comparing the Yelp racial group variables and the PPP racial group variables and results are reported in Appendix Table A3. While we occasionally mismeasure the racial groups, overall, our race proxy based on Yelp information is highly and positively correlated with the true racial category and has a reasonable level of accuracy.[23]

[21] As the application did not ask for demographic information of the business owners, the race and ethnicity information is self-reported by lenders and concentrated among a few lenders (Fairlie and Fossen (2021a)). Coverage of the race and ethnicity information increases in later periods when the SBA began to pay more attention to the racial gap in the loan distribution.

[22] Some examples are African, Somali, and Soul Food as African American; Asian Fusion, Japanese, Chinese, and Pakistani as Asian; Acai Bowls, Caribbean, and Mexican as Hispanic.

[23] Panel A of Appendix Table A3 shows that around 80.1%, 51.9%, and 89.6% of the African, Hispanic, and Asian restaurants based on the Yelp information have an owner of the same racial group according to the PPP information, respectively. Panel B reports that around 61.5%, 16.2%, and 62.0% of the African Americans, Asians, and Hispanics own a restaurant of the corresponding type. The main false negative comes from African Americans owning a

The concurrent literature addresses the data incompleteness of demographic information by conducting zip-code/county level analysis (Erel and Liebersohn 2020; Fairlie and Fossen 2021a), restricting to the subset of PPP recipients with demographic information (Atkins, Cook, and Seamans 2021), estimating the racial group based on borrower name and location (Howell et. al. 2020). One distinct paper is Chernenko and Scharfstein (2021) that links the PPP data with restaurant licenses and voter registrations in Florida and identifies the race and ethnicity group of restaurant owners using the registration information. As independent research, we also link the PPP data to other data sources to identify minority-owned businesses. Unlike Chernenko and Scharfstein (2021), our sample covers all 50 states and Washington, D.C. The wide geographic scope of our sample and the fact that we do not rely on location information when building the proxy allows us to investigate racial disparities across different locations as well as in the same location.

Third, we use the customer ratings from yelp.com to gauge the the minority-non-minority gap between fintech and non-fintech borrowers. Yelp ratings are used as a proxy for operational performance (Bernstein and Sheen 2016) and shown to be related to revenue increase (Luca 2016).[24] The fact that Yelp ratings have a uniform range from 0 to 5 provides a comparable way to investigate disparities in the valuation across lenders for borrowers of different racial groups. We collect the full history of the ratings and construct a restaurant-month panel by taking the average of ratings in each month for each restaurant.

Using a panel of the ratings has the benefits of the possibility of controlling for time trends in ratings by including monthly fixed effects. In addition, it allows us to look at the operational performance both for the period before the Covid-19 crisis and the period during the Covid-19 crisis. It is important to distinguish between the operational performance before and during the pandemic for our study. Restaurants may differ in the change of operational performance due to the Covid-19 crisis, which may result in variation in the degree of difficulties when seeking the PPP loan from traditional and fintech lenders.

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restaurant that was thought to be White. Panel C reports the pairwise correlation between the PPP and Yelp racial group measures, which shows strong and positive correlations, 0.35, 0.52, and 0.68 for African American, Asian, and Hispanic respectively, and statistically significant at the 1% level.

[24] There is recent literature discussing the effectiveness of customer ratings (Mayzlin, Dover and Chevalier (2014)), and using the Yelp ratings as a measure of restaurant sales (Anderson and Magruder (2012)) and visits (Davis et. al. (2019)), and investigating the informativeness of customer ratings in residential home services (Farronato et. al. (2020)), physician choice (Xu, Armony and Ghose (2021)), and books on Amazon (Reimers and Waldfogel (2021)).

Lastly, we merge in other datasets to enrich the scope of our analysis, including other restaurant-level information from yelp.com, 7(a) and 504 program loan-level data from 1990 to 2019, and HUD USPS zip code crosswalk files. In addition, we classify lenders into banks, Certified Community Development Financial Institutions (CDFIs) loan funds/Certified Development Companies (CDCs), and other non-banks. We then match the PPP lenders in our final linked restaurant sample with financial institutions on the Federal Financial Institutions Examination Council (FFIEC) list.[25] Taking advantage of the lender information from FFIEC, we further determine whether the lender is a federally insured institution, a credit union, or a savings & loan association. Details on the lender classification and steps to match with FFIEC are in Online Appendix C2. Details on variable definitions and data sources can be found in Table A1 in the Appendix.

3.2. Sample design

We construct a linked database by matching the borrowers in the PPP dataset to the restaurants on yelp.com. The PPP-Yelp linked dataset offers several advantages. First, it provides information on detailed borrower-level characteristics and a proxy for minority-owned businesses for a representative sample. Second, essentially all restaurants were eligible for PPP while the standard is higher in other industries. Details in the appendix. This rules out the possibility that our results are driven by sample selection bias due to eligibility.[26] Third, the restaurant industry is among the most Covid-19 vulnerable industries. Studying the restaurant borrowers can shed light on how Covid-19 sensitive industries perform during the crisis. Overall, we believe that our linked datasets give us a unique opportunity to study the small business loan market, especially for what drives minority borrowers to use fintech lenders.

We use both code-based algorithms and manual corrections for the matching procedure and employ strict matching criteria that only to include the matches between the PPP recipient and the Yelp-listed restaurant that have meaningful connections in terms of both the name and address. Details on the linking procedure are described in the Online Appendix C3. 104,293 loans are matched to a meaningful link on yelp.com, which account for 28.01% of the whole PPP sample in

[25] We restrict to lenders who lent over 100 loans in the entire PPP program, excluding CDFI, CDC, and non-bank fintech lenders.

[26] For example, if the eligibility is size-based, we would have a different sample of the minority-owned businesses than non-minority-owned businesses that are eligible for the PPP as the minority-owned businesses tend to be smaller.

the *Food Services and Drinking Places* sector. The matching rate is reasonable given that our matching criteria are strict. For the empirical analysis, we focus on the period from April 2018 to March 2021 and limit the sample to restaurants that have at least one rating record since April 2018.[27] Online Appendix C3 also provides a comparison between the linked and unlinked samples which shows a high similarity between two.

3.3. Summary statistics

We mainly use two datasets: one cross-sectional dataset that consolidates the various data sources described above and one restaurant-level panel dataset on historical customer ratings. Our final cross-sectional dataset consists of 98,825 restaurant borrowers in the PPP that are active in business from April 2018 to March 2021.[28] The observation level is a restaurant-lender-loan triplet. The loan and lender characteristics are observed at the PPP loan origination time; the restaurant characteristics are from yelp.com and are observed at the time of data collection (March to July, 2021). The restaurant-level panel dataset provides the monthly average of rating stars for the 98,825 restaurants in our sample from April 2018 to March 2021.

[INSERT TABLE 1 AROUND HERE]

Table 1.1 shows the summary statistics of key variables in the cross-sectional dataset for the borrowers in the 2020 (Panel A) and 2021 (Panel B) waves. We report the results for both the full and the matched samples. The matched sample is constructed by matching minority borrowers with non-minority borrowers in the same state, business type group (aggregated), food price range, and of a similar size with a difference of at most five employees. By employing the matched sample methodology, we take into account the possibility that the above-described matching covariates may affect our results non-linearly.

The recipients in the 2021 wave appear to be different from the recipients in the 2020 wave in our sample. 32% of the 2020 and 38% of the 2021 recipients are minorities; 12% in 2020 and 6% in 2021 are in franchise chains; 9% in 2020 and 17% in 2021 use fintech lenders; 3% in 2020 and 2% in 2021 have lending relationships. The average borrower in 2020 (2021) has 18.62 (9.39)

[27] This deletes about 2.88% of the observations in the linked sample.
[28] We further exclude a total of less than 2% of the observations of non-restaurants, restaurants located in Puerto Rico, Northern Mariana Islands, Guam, and U.S. Virgin Islands, and where one Yelp link is matched to multiple loans.

employees, waits 26.87 (41.12) days for loan approval, and has a total number of 52.08 (33.01) customer reviews during the period from April 2018 to March 2021. Overall, the 2021 wave tends to contain a larger part of financially disadvantaged borrowers than the 2020 sample.

When comparing the full and matched samples, in 2020, the minority and racial group variables are close, with a slightly higher share of Asian-owned restaurants in the matched sample. In other dimensions, restaurants in the matched sample have fewer employees, less business capital, more days to gain an approved loan, are less likely to be franchised, more likely to use fintech lenders, have similar lending relationships, and are matched with lenders with a larger geographic lending scope. Similar patterns hold for the 2021 wave, except that approval days are slightly lower for the matched sample in 2021. These differences in the full and matched samples are consistent with the minority-owned businesses being in a disadvantaged location and business status.

Table 1.2 shows the summary statistics of rating stars in the panel dataset for the borrowers in the 2020 (Panel A) and 2021 (Panel B) waves. The ratings are quite similar for the full and matched sample. However, the average rating is higher during the Covid-19 period (3.92 for the 2020 recipients and 4.06 for the 2021 recipients) than (3.84 for the 2020 recipients and 3.95 for the 2021 recipients). These numbers also mean that the 2021 recipients have higher ratings than the 2020 recipients on average. The differences between the 2020 and 2021 recipients are worth noticing as the latter are more likely to be minority-owned, smaller but of higher ratings.

4. Existence of Racial Disparities

This section investigates whether there is a systematic difference in the usage rate of fintech versus traditional lenders in the PPP program for minority- and non-minority-owned restaurants.

4.1. Fintech lenders in the PPP program

In this subsection, we illustrates the usage of fintech and non-fintech lenders for minority- and non-minority-owned restaurants.

[INSERT FIGURE 3 AROUND HERE]

Figure 3 shows the daily dollar value of loans processed by fintech lenders (Panel (a)) and non-fintech lenders (Panel (b)) for minority- and non-minority-owned restaurants. In the first tranche, major fintech lenders were only allowed to participate in the PPP program in 2020 one week after the initial launch.[29] Before the entry of major fintech lenders on April 10, 2020, there is an enormous gap between the dollar value of loans disbursed to minority- and non-minority-owned businesses. For example, on the first day, the dollar value of loans disbursed by traditional lenders to the minority-owned businesses is only 7.54% of the dollar value disbursed to the non-minority-owned businesses. In contrast, fintech lenders processed more than three million dollars of loans for minority borrowers on the first day of entry, about 35.96% of the dollar value fintech lenders disbursed to non-minority borrowers.

In the second tranche that started on April 27, 2020, traditional lenders covered a relatively larger share of minority-owned businesses than in the first tranche, consistent with findings using the early data release of the subsample of larger loans (Fairlie and Fossen 2021a). However, the gap between fintech and traditional lenders is still prominent, with a 53.38% minority-non-minority ratio for traditional lenders and a 75.27% minority-non-minority ratio for fintech lenders as measured by dollar value. Figures plotting the daily *number* of loans processed by fintech and traditional lenders show a similar pattern and are in the Online Appendix A Figure A1.

We further decompose the minority-owned businesses into African American-, Asian-, and Hispanic-owned businesses and plot the daily disbursed dollar value by fintech and non-fintech lenders in the Online Appendix A Figure A2. The patterns look analogical across the three racial groups, especially after the entry of major fintech lenders, suggesting that fintech lenders serve as a crucial channel of accessing PPP loan for all the three groups.

4.2. Geographic variation in fintech lending

In this subsection, we explore the geographic variation in fintech lending in the PPP program.

[INSERT FIGURE 4 AROUND HERE]

Figure 4 plots the state-level minority shares separately for fintech loans and non-fintech loans. Figures 4(a) and 4(b) plot the minority share for fintech loans and figures 4(c) and 4(d) for non-fintech loans in 2020 and 2021, respectively. The cross-state variation in the minority shares

[29] https://www.lendacademy.com/fintech-lenders-can-finally-apply-to-be-part-of-the-ppp/. Some fintech lenders participated in SBA 7(a) programs before 2020, and therefore were allowed to process PPP loans from the beginning. In our sample, fintech lenders that processed loans before April 10, 2020 are Celtic Bank Corporation, Cross River Bank, Readycap Lending, L.L.C., and Sunrise Banks, National Association.

for non-fintech loans are moderate. In contrast, we observe a larger dispersion across states in minority shares for fintech loans. These results suggest that fintech and non-fintech lenders play a different role in providing credit to minority-owned businesses. All patterns are similar when we use the total *number* of loans to measure minority shares, as shown in Online Appendix A Figure A3.

4.3. Fintech lenders and minority borrowers

Next, we investigate whether minority-owned restaurants are more likely to use fintech lenders in the PPP program in a regression framework. We estimate the following specification:

$$I(Fintech)_{i,c} = \beta I(Minority\ Group)_i + \gamma X_i + \mu_c + \varepsilon_{i,c}$$

where the main dependent variable is a dummy variable equal to one if the restaurant owner *i* borrows from a fintech lender in the PPP program and 0 otherwise. The main independent variables, *African American*, *Asian*, and *Hispanic*, are dummy variables equal to one if the restaurant owner *i* is African Americans Asian, or Hispanic and 0 otherwise. The omitted category is other racial and ethnic groups, mainly composed of White-Americans.

To control for other borrower characteristics to the greatest extent possible given the available data, we include *Employment* for business size, *I(Franchise)* for whether the business is a franchised brand, *Business Type Dummies* for different company organizational formats such as Corporation, L.L.C., Sole Proprietorship, and Self-Employment (Details in Appendix-Table A1). We include city fixed effects (μ_c) to control for time-invariant variation in local economic exposure to the Covid-19 shock and pre-pandemic conditions that might affect the propensity to get a fintech loan. Standard errors are clustered at the city level.

[INSERT TABLE 2 AROUND HERE]

Table 2 columns (1) through (4) present the results on the 2020 wave. Column (1) shows that African American- and Asian-owned restaurants have an 8.00% and 7.43%, correspondingly, higher likelihood of using a fintech lender. However, for Hispanic borrowers, the difference in the likelihood of using fintech and traditional lenders is only 0.88%, which is small in terms of economic magnitude. Coefficients are statistically significant at the 1% level for all groups.

In column (2), we control for city fixed effects and compare the characteristics of business owners in the *same city* who borrow from different lenders. The coefficient before the *African American* dummy decreases to 4.99%, which is around 37.63% of the coefficient without city fixed effects. The coefficient before the *Asian* dummy also decreases and becomes 18.30% of the coefficient without city fixed effects. The coefficient before the *Hispanic* dummy is negligible and statistically insignificant when controlling for city fixed effects. The large reduction in the economic magnitude and statistical significance of the coefficients when controlling for city fixed effects suggests that the geographic variation across cities explains a large part of the higher likelihood of using fintech lenders by minority-owned businesses. Results are robust when using the matched sample and are presented in columns (3) and (4).

Columns (5) through (8) present the results of the 2021 wave. Like the 2020 wave, we observe that minority-owned businesses have a higher likelihood of using fintech lenders. The economic magnitude is even larger than for the 2020 wave. For example, column (5) shows that the coefficients before *African American*, *Asian*, and *Hispanic* dummies are 2.02, 1.36, and 5.63 times as large as the coefficients in the 2020 wave, respectively. In addition, cross-city variation also plays an even larger role in the 2021 wave. As shown in column (6), the coefficient before the *Asian* dummy decreases to 6.10%, the coefficient before the *African American* dummy becomes insignificant, and the coefficient before the *Hispanic* dummy decrease to 3.31%. These results suggest that the role of within-city variation in lender choices is reduced in the 2021 wave. Results are robust when using a matched sample, as reported in columns (7) and (8).

In all specifications, *Employment Size* is negatively related to the propensity to use fintech lenders, which is consistent with the existing papers showing that banks prioritize larger customers (Balyuk, Prabhala, and Puri 2020; Humphries, Neilson, and Ulyssea 2020). Franchised restaurants also tend to be less likely to apply for a PPP loan through fintech lenders, which is as expected given that their parent companies have stronger relationships with banks.

Taken together, our evidence supports the argument that minority-owned businesses are more likely to use fintech lenders than traditional lenders. We find that this effect is the strongest for African Americans, followed by Asians and then for Hispanics. To a large extent, the higher likelihood of using fintech lenders by minority-owned businesses is attributed to regional variation, which tends to have historical roots such as "bank deserts" on the lender side (Erel and Liebersohn 2020; Wang and Zhang 2020) and language and business capital weakness on the borrower side.

These historically rooted factors are hard to eliminate in a short period of time. Moreover, consistent with Chernenko and Scharfstein (2021) and Howell et. al. (2021), we still observe racial disparities after controlling for city fixed effects, suggesting culture- and attitude-based racial bias plays an important role in the outcome of PPP loan distribution.

Encouragingly, we do observe an improvement in terms of racial inequality in the loan distribution process in the 2021 wave. The economic magnitude of the likelihood of using fintech lenders is larger in the 2021 wave than in the 2020 wave, consistent with a learning effect within the minority communities in order to access the government fund. Moreover, the within-city variation also contributes to the racial disparity in fintech usage by a smaller degree in the 2021 wave, suggesting that the unequal access to PPP loans driven by racial bias is also likely to be reduced.

4.4. Minority-non-minority rating gap

We next explore the existence of racial bias through the lens of Yelp ratings. Motivated by our matching game model, we investigate whether minority-owned restaurants are more valued with fintech lenders than with non-fintech lenders based on the operational performance of restaurants.

[INSERT TABLE 3 AROUND HERE]

Table 3 regresses the Yelp ratings on the interaction term between the fintech lender indicator and the three minority racial group indicators respectively, which compares the minority-non-minority rating gap between fintech and non-fintech borrowers. Panel A presents the results for the 2020 wave, and Panel B for the 2021 wave. The dataset is a restaurant-month panel where the dependent variable is the monthly average of customer ratings for a given restaurant. The key independent variable is the interaction terms between the fintech indicator and the three racial group indicators. We also control for the indicators themselves as well as borrower characteristics, which are time-invariant variables. We account for within-restaurant correlation in errors by clustering all panel regressions by restaurants. In each panel, columns (1) through (4) report the results for the pre-Covid period from April 2018 to March 2020, and columns (5) through (8) for the during-Covid period from April 2020 to March 2021.

In the 2020 wave, Panel A columns (1) through (4) show that the coefficients before the interaction terms between the fintech lender indicator and the African-American indicator are insignificant when using ratings from the pre-Covid period. However, as shown in columns (5) through (8), when using ratings during-Covid, the coefficients before the interaction terms are negative and statistically significant at the level of 5%. For example, in column (5), the rating gap between African-American- and non-minority-owned restaurants is 0.25 stars (or 6.5% of the sample mean) more negative for the borrowers of fintech lenders than for the traditional lenders. The difference in the results using the pre- and during-Covid period suggests that the African-American-owned small businesses that were hit especially hard by the Covid-19 crisis (Fairlie 2020; Couch, Fairlie, and Xu 2020) experienced relatively more difficulties in getting a PPP loan from traditional lenders. For Asian-owned restaurants, we find a more negative minority-non-minority rating gap using both the pre- and during-Covid period. For example, in column (1), the rating gap between Asian- and non-minority-owned restaurants is 0.08 stars (or 2% of the sample mean) more negative for the borrowers of fintech lenders than for the traditional lenders. Results of the Hispanic-owned restaurants are insignificant. Results with and without city fixed effects are similar, suggesting that racial disparities exist both across and within cities. Results using the matched sample are robust.

We observe different results in the 2021 wave. The coefficients before the interaction terms between the fintech and racial group indicators for African-American- and Asian-owned restaurants become insignificant, yet for Hispanic-owned restaurants, we observe negative coefficients before the interaction terms when using ratings of the during-Covid period. For example, Panel B column (5) shows that the rating gap between Hispanic- and non-minority-owned restaurants is 0.18 stars (or 4.6% of the sample mean) more negative for those who use fintech lenders than for those who use traditional lenders. Results are robust with or without city fixed effects and when using the full or matched sample.

The difference in the rating gap between the 2020 and 2021 waves implies a shift in the segment of borrowers covered by fintech lenders as we look at the first-time loan recipients instead of the re-applications in both waves. One possible explanation is that Africans and Asians are more familiar with fintech lenders and start using them in the 2020 wave. As most of the African American and Asian borrowers in the blind zone of traditional lenders already participated in the PPP program in 2020, the additional part of the African and Asian borrowers in the 2021 wave via fintech lenders are similar to non-minority borrowers. Hispanics might have been less aware of fintech lending before. However, through the massive media coverage of fintech in PPP, and through the stories from other minority-owned businesses, a greater number of Hispanic borrowers neglected by traditional lenders applied for PPP loans via fintech lenders in 2021.

In Online Appendix Table B3, we do the same analysis but employ one dummy variable, *Minority*, that equals one if the restaurant *i* is a minority-owned restaurant and 0 otherwise. Results are consistent with the findings presented here. Table B4 presents the results where we run regressions on separable subsamples of fintech and non-fintech borrowers. We find that the minority-non-minority rating gap is positive, or less negative, for traditional lenders, which is consistent with traditional lenders having higher requirements for minority borrowers than non-minority borrowers, explicitly or implicitly through selection effects in matching.

Overall, we find that a smaller minority-non-minority rating gap for fintech users, suggesting that minority-owned businesses are less undervalued when matched with fintech lenders. Our evidence implies that non-minority-owned businesses can access the traditional credit market more easily. For minority-owned businesses with a similar rating level, they might have to turn to new technology-based lenders, such as fintech lenders.

4.5. Lender heterogeneity

We further explore heterogeneity among lenders by running the same regression specifications as in Table 3 but using a series of dummies, one for each lender. We focus on the four biggest fintech lenders: Cross River Bank, Kabbage, Square, and Paypal, and the seven largest banks: JPMorgan, Bank of America, Wells Fargo, U.S. Bank, Truist, PNC, and TD Bank. We set the threshold of big lenders where each lender covers at least 1% of the observations in our restaurant-month panel dataset of ratings.[30]

[INSERT FIGURE 6 AROUND HERE]

Figure 6 shows the results for the largest minority group in our sample: Asian-owned restaurants. Consistent with the pooled-lender regression results, the Asian-non-minority gap in

[30] Cross River Bank, JPMorgan, Bank of America, and Wells Fargo each cover about 2.20%, 4.74%, 6.96%, and 4.26% of the observations, and other lenders cover a share of 1%-2% of the observations per lender.

ratings is negative for the 2020 wave for all fintech lenders compared with non-fintech lenders, except for that the rating gap is slightly positive for Cross River Bank using ratings during the Covid-19 period. Overall, smaller fintech lenders tend to have a more negative rating gap, indicating a larger financial inclusion role of smaller lenders for minority-owned businesses.

In contrast, smaller banks tend to display higher racial bias. For the largest three banks, JPMorgan, Bank of America, and Wells Fargo, the rating gap is either small or not significantly different from zero, suggesting that big banks provide credit to a similar group of minority- and non-minority-owned restaurants in terms of rating levels. For relatively "small" big banks, the rating gap is positive and large.

In 2021, there is no clear difference between fintech lenders and banks. This aligns with our pooled-lender regressions and implies an improvement in 2021 that fintech and non-fintech lenders provide credit to a similar segment of minority- and non-minority-owned businesses. This change may be the result of lenders' reaction to media pressure in reducing racial discrimination. It can also be attributed to the less demanding credit needs of borrowers so that the constraints for minority borrowers are relaxed.

Online Appendix Figure A4 and Figure A5 present plots for the African Americans and Hispanics, respectively, where the patterns are also consistent with our results of the pooled-lender regressions.

5. Sources of Racial Disparities

In this section, we investigate the sources of friction that contributes to racial disparities in fintech usage we observe in the PPP program.

5.1. Differences in the rating levels across racial groups

First, in our matching game model, the higher likelihood of fintech usage among minority-owned restaurants can be generated through the combination of the self-selection effect or the crowding-out effect and the difference in rating levels across racial groups. We have the self-selection effect of higher-rated borrowers into fintech lenders if higher-rated borrowers have a higher payoff when matched with fintech lenders than with banks. Similarly, higher-rated borrowers without bank lending relationships are crowded out to fintech lenders by lower-rated borrowers with bank lending relationships due to the additional utility generated by lending relationships. If minority-owned restaurants have higher ratings on average, then we expect to see more minority-owned restaurants using fintech lenders.

However, we find little empirical evidence supporting this channel. On one hand, Table 3 shows that borrowers with higher ratings are more likely to use fintech lenders in the 2020 wave. The coefficient on the fintech indicator is positive and statistically significant at 1% in all specifications, which is consistent with our model's prediction that higher-rated borrowers self-select into fintech lenders or the prediction of the crowding-out effect of lower-rated borrowers with lending relationships.[31] The coefficient on the fintech indicator becomes insignificant in the 2021 wave. As the 2021 wave is a supplement to the 2020 wave, it is reasonable that the effect is attenuated. On the other hand, for Asian- and Hispanic-owned restaurants, the rating levels are lower on average and therefore are not consistent with the prediction of higher usage of fintech lenders. African-American restaurants in the 2020 wave have a higher rating level on average in the pre-Covid period, but the rating difference becomes insignificant during the Covid-19 pandemic.

5.2. Minority borrowers and previous lending relationships

Second, it is possible that a smaller share of minority-owned restaurants have lending relationships, and therefore the minority-owned restaurants are relatively more affected by the crowding-out effects of restaurants with lending relationships. This explanation speaks to one type of racial inequality in the small business credit market that is caused by previous lending relationships. We test this hypothesis by comparing the share of borrowers with lending relationships for minority- and non-minority-owned restaurants.

[INSERT TABLE 4 AROUND HERE]

Table 4 reports the results for the matched sample for the 2020 (Panel A) and 2021 (Panel B) waves. In the 2020 wave, the minority recipients, compared with non-minority recipients, are less

[31] Without further information, we cannot empirically distinguish between the two explanations.

likely to have previous lending relationships and have less intensive lending relationships. Column (1) shows that after controlling for other business characteristics, Asian (Hispanic)-owned restaurants are 0.72% (1.11%) less likely to have lending relationships, amounting to 24% (37%) of the sample mean, where lending relationships are proxied by a dummy variable that equals one if the borrower has at least one SBA 7(a) or 504 loan from 2009 to 2019. In column (2), we further control for city fixed-effects, and the likelihood difference enlarges to 1.00% for Asian-owned restaurants but narrows to 1.03% for Hispanic-owned restaurants. In columns (3) and (4), we measure the intensity of lending relationships using the number of the previous SBA 7(a) and 504 loans the borrower had during 2009-2019. In columns (5) and (6), we build the measure using the dollar value of the previous SBA loans. Results are similar to specifications using the dummy variable of lending relationships. Coefficients before the racial groups become insignificant in most specifications in the 2021 wave. Results for the full sample are reported in Online Appendix Table B6 and are similar.

[INSERT TABLE 5 AROUND HERE]

Moreover, Table 5 shows that restaurants without lending relationships are more likely to use fintech lenders in both the 2020 and 2021 waves. The substitution effect is even stronger in the 2021 wave. Results are consistent across different measures of the lending relationships. Table 5 presents results on the matched sample and Online Appendix Table B7 presents results on the full sample where we observe a similar substitution effect of fintech lenders for borrowers without lending relationships.

Combining these two pieces of evidence, our findings support that the share of borrowers with lending relationships leads to a difference in the fintech usage rate. Overall, we find that minority borrowers have a lower level of previous lending relationships in the SBA programs, and borrowers without lending relationships are more likely to substitute traditional lenders with fintech lenders.

5.3. Business capital of borrowers

Third and perhaps more important, our model predicts that the racial bias in the value of the borrower-lender matches leads to a difference in the minority-non-minority rating gap between fintech and non-fintech lenders. In the previous section, we provide empirical evidence on the existence of such a double difference in rating levels. In this section, we further explore what contributes to the existence of racial disparities.

In the preference for technology scenario, our model predicts that a larger difference in the preference for technology between the minority and non-minority borrowers will translate into a larger difference in the minority-non-minority rating gap between fintech and non-fintech lenders. As there is no good measure of the preference for technology, we cannot directly test this prediction. Instead, we indirectly test the hypothesis by studying whether an increase in the level of the business capital by the borrower mitigates the difference in the minority-non-minority rating gap between fintech and non-fintech lenders.

Minority-owned restaurants tend to have a business model that is more informal and less familiar to outsiders. Because business capital can provide more information about the restaurant, it can be soft assets that serves as a role of collateral (Hochberg, Serrano, and Ziedonis, 2018; Davis, Morse, and Wang, 2020). As a result, borrowers with a higher level of business capital can rely less on technology in the lending process. In other words, the business capital of borrowers may be a way to mitigate the racial bias in the small business lending market.

We use the total number of ratings during our entire analysis sample period from April 2018 to March 2021 as a proxy for business capital.[32] For two otherwise similar restaurants, the one with more reviews has more available information and can be seen as having a better reputation.

[INSERT TABLE 6 AROUND HERE]

Table 6 reports the results on the role of business capital for the matched sample. The coefficients before the triple interaction between the fintech lender indicator, the minority borrower indicator, and business capital are positive and significant at the 1% level in all specifications for Asian- and Hispanic-owned restaurants in the 2020 wave. Column (1) shows that an increase of 100 reviews during our entire analysis sample period, which amounts to around one unit of sample deviation, is associated with a 0.11 star (or 1.38 times the original racial gap) smaller fintech-minority rating gap for the Asian recipients in the 2020 wave. Column (2) controls

[32] Shi (2021) uses the firm size as a proxy for business capital to study how business capital increases the likelihood of being a PPP recipient.

for city-month fixed effects and the results are similar. In columns (3) and (4), we measure the racial gap using ratings for the during -- Covid period and the results are robust.

Columns (5) through (8) present the results for the 2021 wave where we observe coefficients of almost twice as big as the coefficients in the 2020 wave for Asian-owned restaurants. Coefficients before the triple interaction terms with Hispanic-owned restaurants become insignificant. Results on the full sample are reported in the Online Appendix Table B8 and are consistent.

Overall, our findings suggest that restaurants with a higher level of business capital are associated with a lower level of racial discrimination. This is in alignment with a racial gap in tech-preference on the borrower side contributing to the difference in the minority-non-minority rating gap between fintech and non-fintech lenders.

5.4. Geographic scope of lenders

Finally, another prediction in the lending relationship scenario in our model is that the difference in the value of lending relationships between the minority and non-minority borrowers is also positively related to the minority-non-minority rating gap between fintech and non-fintech lenders. We test this hypothesis by investigating whether a decrease in the level of the lender attention aggravates the difference in the minority-non-minority rating gap between fintech and non-fintech lenders.

Discrimination can result in a lower value of lending relationships for minority-owned businesses. As the value of lending relationships tends to be formed and reinforced through interactions, less lender attention allocated to the region where the borrower is located can exaggerate the racial gap in the value of lending relationships. As a result, we observe a larger racial gap for lenders with a lower level of attention to individual borrower regions.

We use the relative geographic lending scope (GS_r) as a proxy for the relative lender attention allocated to a given geographic region. GS_r is calculated as the total number of zip codes divided by the total number of cities that the lender covers in the entire PPP loan sample. For this part of the analysis, we drop CDFIs/CDCs as they may have specific regional requirements.

[INSERT TABLE 7 AROUND HERE]

Table 7 reports the results on the impact of relative geographic lending scope (GS_r) for the matched sample. The coefficients before the triple interaction between the fintech lender indicator, the minority borrower indicator, and GS_r are negative in specifications with a significance level of at least 5%. Column (1) shows that an increase of one location of GS_r is associated with a 0.06 star (or 0.75 times the original racial gap) larger fintech-minority rating gap for the Asian recipients in the 2020 wave. Results with and without city-month fixed effects are similar. In addition, results on the full sample are reported in the Online Appendix Table B9 and are consistent.

To further demonstrate that it is the *relative* geographic lending scope that affects the racial bias, we re-do the analysis by including both the geographic lending scope at the city level (GS_{city}) and the geographic lending scope at the zip-code level (GS_{zip}). Results are presented in Online Appendix Table B10. Consistent with the results using the relative geographic lending scope (GS_r), the coefficients are positive for the triple interaction with GS_{city} and negative for the triple interaction with GS_{zip}.

Overall, our findings indicate that restaurants matched with lenders with a higher level of attention in their geographic area are associated with a lower level of racial discrimination. This is consistent with the existence of a racial bias in the value of lending relationships.

6. Alternative Explanations

6.1. Other lender types

In this section, we study other types of lenders, including first-time banks, credit unions, community development financial institutions and community development corporations, non-federally-insured lenders, and Savings & Loan Associations, to see if non-technology-related features of fintech lenders coincidentally lead to our main empirical findings.[33]

6.1.1. First-time bank participants

[33] For demonstration purposes, we present the results of the rating gap using the matched sample. Results on the full sample are in Online Appendix Table B11 and are in alignment with the findings for the matched sample.

First, it is possible that fintech lenders are new entrants to SBA programs and therefore attract a different segment of borrowers. We test this hypothesis by studying the 672 first-time participants out of the 4,131 PPP bank sample, which account for around 4.04% of the loans.

[INSERT TABLE 8 AROUND HERE]

We do not find supporting evidence. Table 8 Panel A shows that the relationship between minority borrowers and the likelihood of being matched with newly entered banks is significantly lower for Asian-owned restaurants and insignificant for African American- and Hispanic-owned restaurants. Moreover, Panel B shows that the minority-non-minority rating gap is insignificant or more positive for fintech lenders compared with non-fintech lenders. The results indicate that, unlike fintech lenders, if anything, first-time banks attract a segment of higher-rated minority-owned restaurants than non-minority-owned restaurants.

6.1.2. Credit unions

Second, it is possible that, because fintech lenders tend to have more flexible loan terms than banks, they may develop a different customer base. We test this hypothesis by studying another type of bank alternatives: credit unions. Credit unions are the second largest type of bank alternatives among PPP lenders, composing 409 out of the 3,658 lenders that we find a match with FFEIC, accounting for 3.48% of the loans. If our documented minority-non-minority gap is because of the unobserved characteristic of borrowers that prefer lenders offering more attractive loan terms, (and not due to racial discrimination), we should observe a similar pattern for the comparison between credit unions and banks as for the comparison between fintech lenders and banks.

[INSERT TABLE 9 AROUND HERE]

Table 9 Panel A shows that Asian-owned restaurants are less likely to use credit unions, which is opposite of the results for fintech lenders. African American- and Hispanic-owned restaurants are more likely to use credit unions. However, Panel B reports a more negative difference in the minority-non-minority rating gap between fintech and non-fintech lenders for Asian-owned restaurants. The same signs of the coefficients of the credit union usage likelihood and the double difference in rating levels suggest that the segment of minority borrowers served by credit unions are those who have a better evaluation with banks, rather than those who are more undervalued. We do not find the same results for credit unions as for fintech lenders.

6.1.3. Community development financial institutions/corporations

Third, we investigate whether fintech lenders mimic the role of community development financial institutions (CDFIs) and community development corporations (CDCs). There are 54 CDFIs/CDCs in the sample of 4,185 lenders, accounting for 0.72% of the loans. We exclude fintech lenders and other non-banks to make a clean comparison.

[INSERT TABLE 10 AROUND HERE]

At first glance, CDFIs and CDCs play a similar role as fintech lenders. Table 10 Panel A shows that minority-owned restaurants of all racial groups are more likely to use CDFIs/CDCs in the 2020 wave. Results become insignificant and even significantly negative for Asian-owned restaurants in the 2021 wave. However, in Panel B, we find no significant results on the double-difference in rating levels, except for Asians in the 2020 wave using the pre-Covid ratings. Our findings imply that while CDFIs and CDCs are able to cover more minority-owned businesses, they play a limited supplemental role in extending credits to minority-owned businesses that are more undervalued by traditional lenders.

6.1.4. Non-federally-insured lenders and Savings & Loan Associations

In addition, we present results on two other types of lenders that might play a similar role as fintech lenders in the Online Appendix: the 11 non-federally-insured lenders (Table B12) and the 25 Savings & Loan Associations (Table B13).

First, our racial disparity results might be driven by regulatory differences in federally-insured and non-federally-insured lenders.[34] For example, minority borrowers might have received

[34] The PPP Lender Information Sheet states that all federally insured depository institutions, federally insured credit unions, and Farm Credit System institutions are eligible to participate in this program. For non-insured lenders, as most fintech lenders are, they need to apply for approval to be enrolled in the program.
https://home.treasury.gov/system/files/136/PPP%20Lender%20Information%20Fact%20Sheet.pdf

information about PPP loans later and applied after more non-insured lenders participated. Second, fintech lenders are also well-known as an alternative option of mortgages and might be more familiar to lower-rated minority-owned businesses. To address this possibility, we study Savings & Loan Associations (S&Ls) who mainly offer affordable mortgages as a comparison group to banks. However, we do not find similar patterns for non-federally-insured lenders or S&Ls as for fintech lenders. If anything, we find a more positive difference in the minority-non-minority rating gap between fintech and non-fintech lenders.

To recap, in this section, we show that for other types of lenders, there is no consistent evidence that supports our model's prediction on the negative double difference in rating levels. Unlike fintech lenders, we do not find evidence that first-time bank participants, credit unions, CDFIs/CDCs, non-federally-insured lenders, or S&Ls are likely to provide credit accesses to the segment of minority borrowers that are more undervalued in the traditional market.

6.2. Loan approval speed

Another alternative explanation of our racial disparity results is a difference among borrowers in the preference of loan processing speed that coincides with using fintech lenders. Online Appendix Table B14 shows that on average fintech lenders have a higher loan processing capacity. In addition, the existing literature documents that fintech lenders process mortgage applications much faster than other lenders (Fuster et. al. 2019). Therefore, it might be that a different group of minority and non-minority borrowers prefer quicker loan processing and turn to fintech lenders disproportionally.

[INSERT TABLE 11 AROUND HERE]

Table 11 shows the regression results that compare the difference in the number of days needed to get the loan approved from the beginning of each PPP wave between the minority and non-minority borrowers matched with fintech and non-fintech lenders.[35] In the 2020 wave, the double difference in approval days is insignificant for the African American- and Hispanic-owned

[35] The measure based on approval dates is not the exact loan processing speed of the lenders. However, we do not have information on the application dates, and the measure using approval dates provides information on borrowers' preference for loan processing speed given that all the loan application starting dates are the same for all lenders.

restaurants. For Asian-owned restaurants, double difference in approval days is positive and significant at the 1% level. For example, column (1) reports that the Asian-non-minority gap in approval days is 2.23 days longer for the fintech borrowers than for non-fintech borrowers. This indicates that minority borrowers who turn to fintech lenders waited relatively longer compared with non-minority borrowers than those who reach out to non-fintech lenders, consistent with a higher barrier that minority borrowers face to access to the traditional credit market.

Interestingly, consistent with a reduction in racial basis in the 2021 wave we document in the previous section using the rating gap, there are also improvements in waiting time. The coefficients before the interaction terms between the racial group and fintech indicators become negative for Asian- (8.11 days shorter) and Hispanic-owned restaurants (8.72 days shorter). Results on African American- owned restaurants are insignificant. One explanation for the shorter waiting period for the 2021 wave could be that fintech lenders improved their loan processing speed, given that fintech platforms are more adaptive for similar lending tasks in the following year. Another is that or the group of minority borrowers supplemented by the 2021 wave were no longer those overlooked by the traditional credit market.

In robustness checks reported in Online Appendix Table B15, we address the issue that fintech lenders were not allowed to participate at the beginning of the 2020 wave. We limit the sample period to 1) after the official approval date of fintech entry, and 2) the second tranche. Results are robust and even stronger when limited to the second tranche.

[INSERT TABLE 12 AROUND HERE]

Table 12 reports results on the robustness check of Table 3 where we control for the approval date fixed effects. This gives the estimation of the double difference in rating levels for loans approved on the same day, and thus rules out differences due to the borrower's position in the PPP application queue. Coefficients before the interaction terms between the racial group and fintech indicators are very close to those reported in Table 3, which implies that the racial disparities that we demonstrate *do not* come from a difference in loans approved earlier or later.

Overall, our findings suggest that minority borrowers turned to fintech lenders in the PPP program *not* because they have a higher preference for getting the loan earlier. In fact, our results show that minority borrowers who applied for a loan through fintech lenders had a longer waiting time in the 2020 wave.

7. Conclusion

This paper studies whether fintech lenders can serve minority-owned small businesses that are less valued in the traditional credit market. We use the Paycheck Protection Program as a laboratory and a linked dataset on the PPP loans and a large-scale national-wide sample of restaurants on yelp.com to study the question.

We first document that minority-owned businesses are more likely to use fintech lenders, which is consistent with the existing literature. More importantly, we provide evidence showing that the racial disparity in using fintech versus traditional lenders is very likely to be attributed to deep-rooted racial gaps in the small business lending market. Compared with fintech lenders, traditional lenders are more likely to lend to minority-owned businesses with previous lending relationships, and of higher ratings. Given the fully government-guaranteed nature of the PPP program, these findings point to unequal credit provision driven by taste-based discriminations.

Whether governments should extend credit access to the minority-owned businesses underserved by traditional lenders is a normative question. On one hand, these minority-owned businesses are of lower rating levels and are likely to have lower revenue (Luca (2016)). On the other hand, they are part of the fabric of their communities, employing local residents and supporting civic causes. Moreover, the existing literature finds that SBA loans have positive effects on firm growth and productivity (Krishnan, Nandy, and Puri, 2015; Brown and Earle, 2017), which implies that the lower operational performance of these minority-owned businesses may exactly due to being previously excluded from government loan programs.

This paper studies the first large-scale government loan program where major fintech lending platforms, such as Paypal, Kabbage, and Funding Circle, are allowed to be eligible lenders. Our study has important policy implications that speak to the debate on whether to allow for the participation of fintech lenders in fully or partially guaranteed government loan programs. Our findings suggest that there are systematic biases and blind spots in the traditional loan distribution channel and that can be covered by fintech lenders. This has implications beyond the Covid-19 period. Whether the credit access provided by fintech lenders improves the financial and operational performance of those underserved borrowers is an interesting topic for future research. In addition, the impact of the introduction of fintech lenders on traditional lenders is also a promising avenue for future research.

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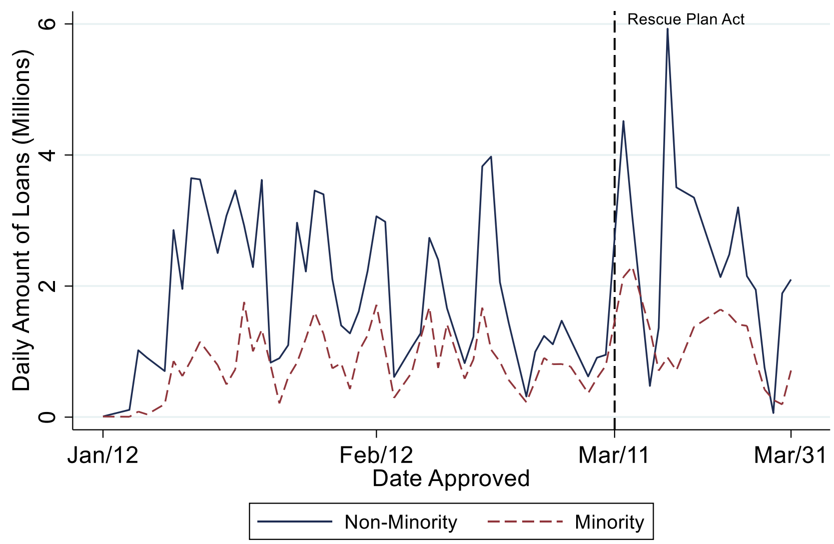
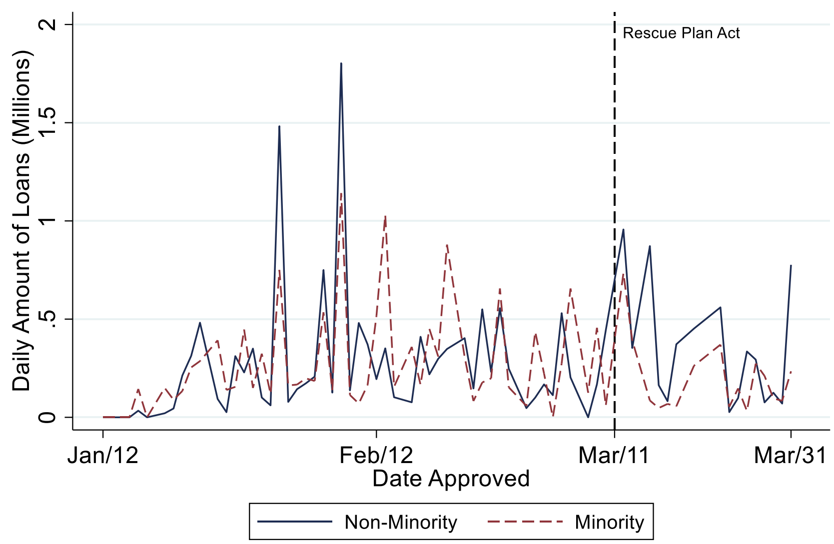
Figures



(a) 2021 PPP, Non-Fintech Lenders



(b) 2021 PPP, Fintech Lenders

Figure 1: Minority- and Non-Minority-owned Businesses in the 2021 PPP Fintech vs. Non-Fintech

This figure plots the daily dollar value of PPP loans received by minority- and non-minority-owned restaurants that were processed by non-fintech (Panel (a)) and fintech (Panel (b)) lenders in the 2021 PPP wave for our sample. The 2021 wave spans the period from January 12, 2021 to March 31, 2021. The y-axis represents the daily dollar value of loans processed (in USD millions), and the x-axis represents the loan approval date. The blue solid line plots non-minority-owned restaurants and the red dashed line plots minority-owned restaurants. The vertical dashed line indicates the implementation of the American Rescue Plan Act of 2021 on March 11, 2021.

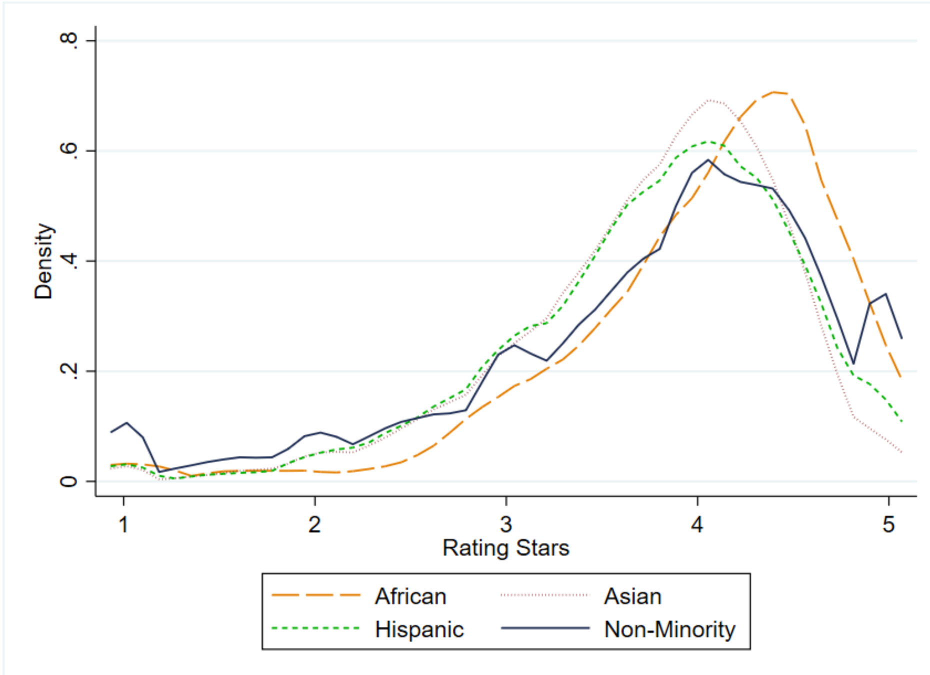
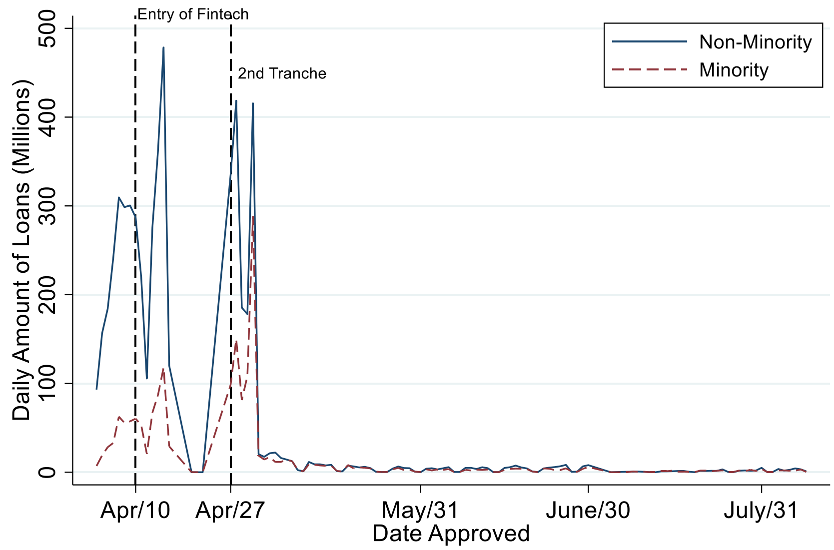
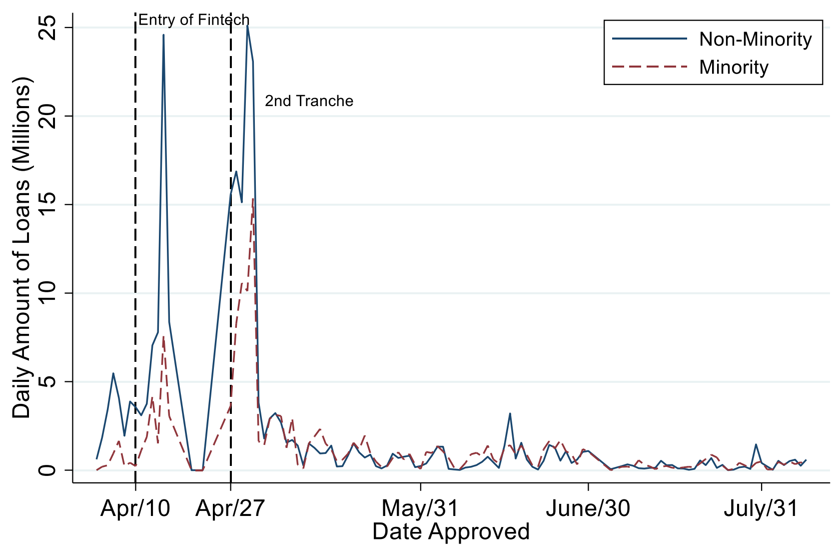


Figure 2: Distribution of Restaurant Ratings across Borrower Racial Groups

This figure plots the density of restaurant ratings for each racial group using data on customer ratings from yelp.com. For each restaurant in our linked sample, we calculate the mean of the monthly average of ratings from April 2018 to March 2021.



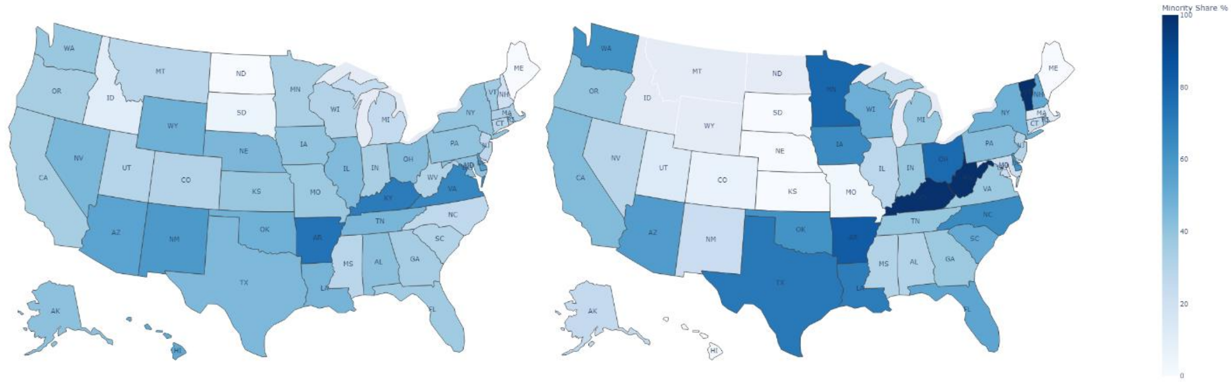
(a) 2020 PPP, Non-Fintech Lenders



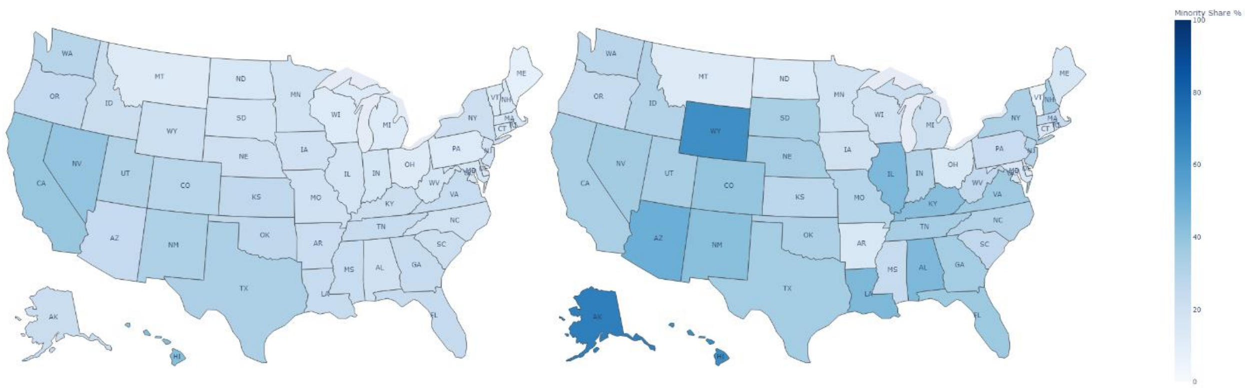
(b) 2020 PPP, Fintech Lenders

Figure 3: Minority- and Non-Minority-owned Businesses in the 2020 PPP Fintech vs. Non-Fintech (Dollar Value)

This figure plots the daily dollar value of PPP loans received by minority- and non-minority-owned restaurants that are processed by non-fintech (Panel (a)) and fintech (Panel (b)) lenders in the 2020 PPP wave for our sample. The 2020 wave spans the period from April 3, 2020 to August 8, 2020. The y-axis represents the daily dollar value of loans processed (in USD millions), and the x-axis represents the loan approval date. The blue solid line plots the non-minority-owned restaurants and the red dashed line plots the minority-owned restaurants. The first vertical dashed line indicates the entry of fintech lenders on April 10, 2020 and the second vertical dashed line indicates the beginning of the second tranche of the 2020 PPP on April 27, 2020.



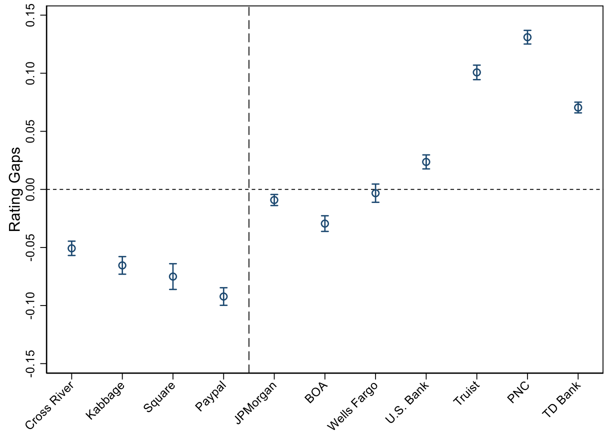
(a) Minority Share (Fintech) in the 2020 PPP (b) Minority Share (Fintech) in the 2021 PPP



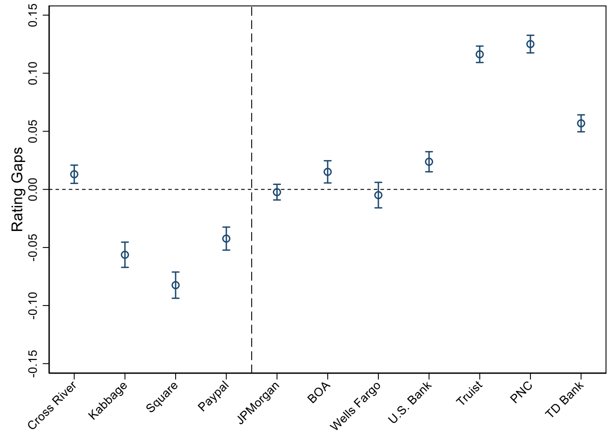
(c) Minority Share (Non-Fintech) in the 2020 PPP (d) Minority Share (Non-Fintech) in the 2021 PPP

Figure 4: Percentage of Loans Distributed to Minority-owned Businesses
Fintech vs. Non-Fintech (Dollar Value)

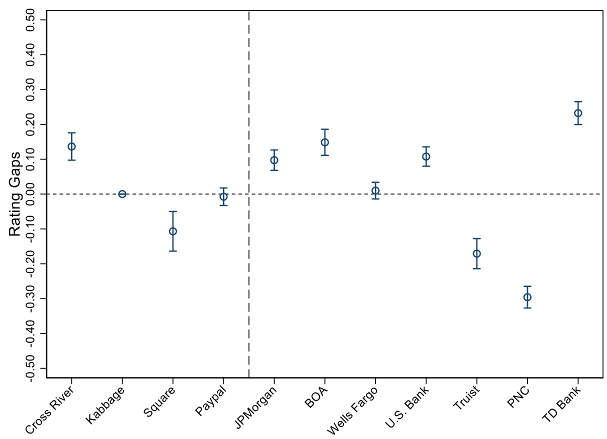
This figure plots the share of loan dollar value distributed to minority-owned businesses processed by fintech (Panels (a) and (b)) and non-fintech (Panels (c) and (d)) lenders in the 2020 and 2021 waves, based on our sample. The *Minority Shares* range from 0% (the lightest blue) to 100% (the darkest blue).



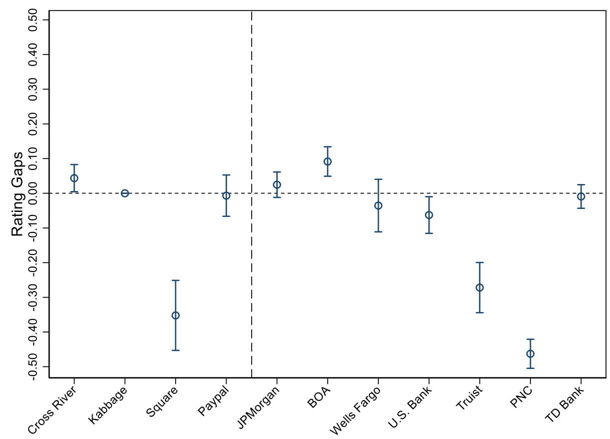
(a) Before-Covid Ratings, 2020 PPP Recipients



(b) During-Covid Ratings, 2020 PPP Recipients



(c) Before-Covid Ratings, 2021 PPP Recipients



(d) During-Covid Ratings, 2021 PPP Recipients

Figure 5: Minority-Non-Minority Rating Gap (Asian-owned)
Fintech vs. Non-Fintech

This figure plots the minority-non-minority rating gap for Asian-owned restaurants in the 2020 wave using historical ratings before the Covid-19 crisis (Panel (a)) and ratings during the Covid-19 crisis (Panel (b)), and for Asian-owned restaurants in the 2021 wave using the before-Covid ratings (Panel (c)) and during-Covid ratings (Panel (d)). The y-axis represents the coefficients before the interaction terms between the racial group indicator and lender indicators from the regressions as in Table 3, except that we decompose the fintech indicator into several dummies for each big fintech lender and bank. The x-axis represents each lender. We plot the biggest four fintech lenders in our sample: Cross River Bank, Kabbage, Square, and Paypal, and the largest seven banks in our sample: JPMorgan, Bank of America, Wells Fargo, U.S. Bank, Truist, PNC, and TD Bank. In each regression, the dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. The *Asian* indicator is defined to be 1 for restaurants that we identify as Asian food restaurants. The *Lender$_j$* (*e,g., Kabbage*) indicator is defined to be 1 for loans backed by that lender (e.g. by Kabbage). The omitted category is all other lenders. Control variables are the same as in Table 3 which contain lender dummies, racial group dummy, employment size, franchise dummy, month-city fixed effects, business type fixed effects, and eating policy dummies. Detailed variable definitions are in Appendix Table A1. Standard errors are clustered at the restaurant-lender level.

Table 1 Summary Statistics

Table 1.1 Restaurant and Lender Characteristics – Cross Section

	Panel A: 2020 PPP First Draw															
	Full Sample								Matched Sample							
	N	Mean	S.D.	Min	P.25	Median	P.75	Max	N	Mean	S.D.	Min	P.25	Median	P.75	Max
I(Minority)	92,557	0.32	0.46	0	0	0	1	1	86,097	0.33	0.47	0	0	0	1	1
I(African Ame.)		0.01	0.08	0	0	0	0	1		0.01	0.08	0	0	0	0	1
I(Asian)		0.18	0.39	0	0	0	0	1		0.20	0.40	0	0	0	0	1
I(Hispanic)		0.13	0.33	0	0	0	0	1		0.13	0.34	0	0	0	0	1
Employment		18.62	31.02	1	5	11	21	500		14.79	17.44	1	5	10	19	500
I(Franchise)		0.12	0.33	0	0	0	0	1		0.11	0.32	0	0	0	0	1
I(Fintech)		0.09	0.29	0	0	0	0	1		0.10	0.29	0	0	0	0	1
Δ(Date)		26.87	24.19	0	10	25	28	127		27.64	24.43	0	11	25	28	127
I(Rel.)		0.03	0.18	0	0	0	0	1		0.03	0.18	0	0	0	0	1
Rel. (N. Loans)		0.04	0.25	0	0	0	0	8		0.04	0.25	0	0	0	0	8
Rel. (A. Loan)		18	3,074	0	0	0	0	680,000		20	3,187	0	0	0	0	680,000
BC		52.08	96.02	1	8	23	59	3,655		50.98	91.22	1	8	23	58	3,655
GS_{zip}		4,236	5,079	1	220	1,295	8,979	16,637		4,362	5,140	1	225	1,354	10,684	16,637
GS_{city}		2,715	3,252	1	159	835	6,096	11,415		2,797	3,294	1	162	886	6,458	11,415
I(New Bank)	82,287	0.04	0.20	0	0	0	0	1	76,082	0.04	0.20	0	0	0	0	1
I(CU)	85,351	0.03	0.18	0	0	0	0	1	79,147	0.03	0.18	0	0	0	0	1
I(CD)	82,821	0.01	0.08	0	0	0	0	1	76,605	0.01	0.08	0	0	0	0	1

Table 1 Summary Statistics (Cont.)

Restaurant and Lender Characteristics – Cross Section (Cont.)

	Panel B: 2021 PPP First Draw															
	Full Sample								Matched Sample							
	N	Mean	S.D.	Min	P.25	Median	P.75	Max	N	Mean	S.D.	Min	P.25	Median	P.75	Max
I(Minority)	6,268	0.38	0.49	0	0	0	1	1	6,024	0.39	0.49	0	0	0	1	1
I(African Ame.)		0.01	0.11	0	0	0	0	1		0.01	0.12	0	0	0	0	1
I(Asian)		0.22	0.41	0	0	0	0	1		0.22	0.42	0	0	0	0	1
I(Hispanic)		0.15	0.36	0	0	0	0	1		0.16	0.36	0	0	0	0	1
Employment		9.39	13.41	1	3	6	11	342		8.41	8.66	1	3	6	10	93
I(Franchise)		0.06	0.23	0	0	0	0	1		0.06	0.23	0	0	0	0	1
I(Fintech)		0.17	0.38	0	0	0	0	1		0.18	0.38	0	0	0	0	1
Δ(Date)		41.12	21.14	0	23	39	60	78		41.01	21.05	0	23	39	60	78
I(Rel.)		0.02	0.13	0	0	0	0	1		0.02	0.13	0	0	0	0	1
Rel. (N. Loans)		0.02	0.16	0	0	0	0	3		0.02	0.15	0	0	0	0	3
Rel. (A. Loan)		0.00	0.06	0	0	0	0	3		0.00	0.06	0	0	0	0	3
BC		33.01	64.64	1	5	14	38	2,095		32.60	59.53	1	5	14	38	2,095
GS_{zip}		5,702	5,875	1	266	3,275	10,972	16,637		5,808	5,893	1	284	3,381	10,972	16,637
GS_{city}		3,707	3,872	1	188	2,200	6,595	11,415		3,775	3,885	1	195	2,225	6,595	11,415
I(New Bank)	4,866	0.04	0.20	0	0	0	0	1	4,648	0.04	0.20	0	0	0	0	1
I(CU)	4,962	0.02	0.14	0	0	0	0	1	4,741	0.02	0.14	0	0	0	0	1
I(CD)	5,299	0.05	0.21	0	0	0	0	1	5,080	0.05	0.21	0	0	0	0	1

Table 1.2 Restaurant Ratings – Restaurant-Level Panel

	Full Sample								Matched Sample							
	N	Mean	S.D.	Min	P.25	Median	P.75	Max	N	Mean	S.D.	Min	P.25	Median	P.75	Max
	Panel A: 2020 PPP First Draw															
	Before Covid-19															
Rating Stars	1,032,002	3.84	1.21	1	3	4	5	5	959,322	3.84	1.20	1	3	4	5	5
	During Covid-19															
Rating Stars	464,639	3.92	1.29	1	3	4	5	5	432,599	3.93	1.29	1	3	4	5	5
	Panel B: 2021 PPP First Draw															
	Before Covid-19															
Rating Stars	51,845	3.95	1.22	1	3	4	5	5	50,103	3.95	1.22	1	3	4	5	5
	During Covid-19															
Rating Stars	26,492	4.06	1.25	1	4	5	5	5	25,477	4.06	1.25	1	4	5	5	5

Table 2 Fintech Lenders and Minority-owned Businesses

This table reports the linear probability regression results where the dependent variable is the *Fintech* loan indicator (0/1). The key independent variables are *African American*, *Asian*, and *Hispanic* indicators that are defined to be 1 for restaurants with the corresponding food type. The 2020 and 2021 PPP waves are indicated in column heads. The matched sample is constructed by matching minority borrowers with non-minority borrowers in the same state, same business type (aggregated), same food price range, and of an employment size with a difference of at most five employees. In addition to the variables reported in the table, we also control for city and business type fixed effects. Detailed variable definitions are in Appendix Table A1. For demonstration purposes, the dependent variable is multiplied by 100. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	*I*(Fintech) × 100							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African Ame.)	8.00***	4.99***	7.64***	4.86***	16.18***	5.52	16.07***	6.62
	(1.59)	(1.67)	(1.64)	(1.71)	(5.05)	(6.08)	(5.07)	(6.01)
I(Asian)	7.43***	6.07***	7.08***	5.84***	10.14***	6.10***	9.60***	5.67***
	(0.38)	(0.40)	(0.38)	(0.40)	(1.33)	(1.80)	(1.34)	(1.82)
I(Hispanic)	0.88***	0.06	0.82**	0.04	4.95***	3.31*	5.04***	3.71*
	(0.32)	(0.32)	(0.32)	(0.33)	(1.42)	(1.93)	(1.44)	(1.98)
Employment	-0.06***	-0.06***	-0.14***	-0.14***	-0.14***	-0.12***	-0.26***	-0.30***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.03)	(0.05)	(0.05)	(0.07)
I(Franchise)	-0.31	-0.23	0.02	-0.16	-2.95*	-7.72***	-2.42	-6.90**
	(0.32)	(0.34)	(0.36)	(0.38)	(1.78)	(2.74)	(1.88)	(2.85)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	92,556	88,873	86,095	82,426	6,266	4,150	6,022	3,984
Adjusted R^2	0.041	0.062	0.042	0.062	0.061	0.078	0.061	0.084

Table 3 Minority-Non-Minority Rating Gap

This table reports the regression results from examining the difference in ratings between minority- and non-minority-owned restaurants that borrow from fintech and non-fintech lenders. In Panels A and B, we report results on the 2020 and 2021 PPP waves, respectively. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The matched sample is constructed by matching minority borrowers with non-minority borrowers in the same state, same business type (aggregated), same food price range, and of an employment size with a difference of at most five employees. In addition to the variables reported in the table, we also control for city × month (or month) fixed effects, business type fixed effects, and eating policy dummies for options of delivery, takeout, reservations, and outdoor seating. Detailed variable definitions are in Appendix Table A1. *Employment* is divided by 100 for demonstration purposes. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw								
Dep. Var.	**Rating Stars**							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(Fintech)	-0.11	-0.09	-0.11	-0.09	-0.25^{**}	-0.23^{**}	-0.24^{**}	-0.23^{**}
	(0.07)	(0.08)	(0.08)	(0.08)	(0.11)	(0.11)	(0.11)	(0.11)
I(Asian) × *I*(Fintech)	-0.08^{***}	-0.09^{***}	-0.08^{***}	-0.09^{***}	-0.06^{***}	-0.04^{*}	-0.06^{***}	-0.04^{*}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
I(Hisp.) × *I*(Fintech)	-0.01	0.01	-0.01	0.01	-0.02	0.00	-0.02	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
I(Fintech)	0.05^{***}	0.06^{***}	0.05^{***}	0.06^{***}	0.05^{***}	0.04^{***}	0.05^{***}	0.04^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
I(African Ame.)	0.12^{***}	0.15^{***}	0.11^{***}	0.14^{***}	0.05	0.06	0.04	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
I(Asian)	-0.09^{***}	-0.07^{***}	-0.09^{***}	-0.08^{***}	-0.03^{***}	-0.03^{***}	-0.04^{***}	-0.04^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
I(Hisp.)	-0.09^{***}	-0.09^{***}	-0.09^{***}	-0.09^{***}	-0.11^{***}	-0.11^{***}	-0.11^{***}	-0.11^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Employment	-0.12^{***}	-0.12^{***}	-0.22^{***}	-0.21^{***}	-0.11^{***}	-0.12^{***}	-0.19^{***}	-0.19^{***}
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
I(Franchise)	-0.89^{***}	-0.87^{***}	-0.88^{***}	-0.85^{***}	-1.06^{***}	-1.02^{***}	-1.05^{***}	-1.00^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Eating Policy Controls	X	X	X	X	X	X	X	X
Observations	1,032,002	974,781	959,322	902,934	464,639	434,948	432,598	403,363
Adjusted R^2	0.046	0.067	0.043	0.064	0.052	0.072	0.048	0.069

Table 3 Minority-Non-Minority Rating Gap (Cont.)

Panel B: 2021 PPP First Draw								
Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(Fintech)	-0.13	-0.31	-0.12	-0.30	-0.14	-0.29	-0.12	-0.26
	(0.17)	(0.20)	(0.17)	(0.21)	(0.18)	(0.21)	(0.18)	(0.21)
I(Asian) × *I*(Fintech)	0.02	0.08	0.03	0.10	-0.02	0.01	-0.00	0.03
	(0.06)	(0.09)	(0.06)	(0.09)	(0.07)	(0.10)	(0.07)	(0.10)
I(Hispanic) × *I*(Fintech)	0.08	0.13	0.08	0.13	-0.18^{**}	-0.28^{**}	-0.19^{**}	-0.27^{**}
	(0.07)	(0.11)	(0.07)	(0.11)	(0.09)	(0.13)	(0.09)	(0.13)
I(Fintech)	-0.06	-0.07	-0.07^{*}	-0.08	-0.06	-0.01	-0.06	-0.02
	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)
I(African Ame.)	0.16	0.31^{**}	0.15	0.31^{**}	-0.05	-0.01	-0.05	-0.01
	(0.11)	(0.13)	(0.11)	(0.12)	(0.11)	(0.13)	(0.11)	(0.13)
I(Asian)	-0.13^{***}	-0.13^{***}	-0.14^{***}	-0.14^{***}	-0.04	-0.01	-0.04	-0.01
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
I(Hispanic)	-0.13^{***}	-0.10^{**}	-0.12^{***}	-0.09^{*}	-0.16^{***}	-0.09^{*}	-0.15^{***}	-0.08
	(0.03)	(0.05)	(0.03)	(0.05)	(0.04)	(0.06)	(0.04)	(0.06)
Employment	-0.34^{***}	-0.32^{**}	-0.72^{***}	-0.82^{***}	-0.38^{***}	-0.42^{**}	-0.60^{***}	-0.82^{***}
	(0.10)	(0.15)	(0.11)	(0.18)	(0.10)	(0.18)	(0.12)	(0.19)
I(Franchise)	-0.91^{***}	-0.84^{***}	-0.88^{***}	-0.79^{***}	-0.91^{***}	-0.81^{***}	-0.90^{***}	-0.77^{***}
	(0.06)	(0.08)	(0.06)	(0.08)	(0.07)	(0.10)	(0.07)	(0.10)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Eating Policy Controls	X	X	X	X	X	X	X	X
Observations	51,844	29,256	50,102	28,211	26,491	14,723	25,476	14,095
Adjusted R^2	0.039	0.049	0.039	0.050	0.041	0.050	0.039	0.047

Table 4 Previous Lending Relationships and Minority-owned Businesses

This table reports the regression results from examining the difference in previous lending relationships between minority- and non-minority-owned restaurants. In Panels A and B, we report results on the 2020 and 2021 PPP waves, respectively. The dependent variable in columns (1) and (2) is a dummy variable that equals 1 if the borrower had SBA 7(a) or 504 loans during 2009-2019. In columns (3) and (4), the dependent variable is the total number of SBA 7(a) or 504 loans during 2009-2019. In columns (5) and (6), the dependent variable is the value (in USD millions) of SBA 7(a) or 504 loans during 2009-2019. *A. Loan* is winsorized at the 1% and 99% cuts. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table A1. For demonstration purposes, all dependent variables are multiplied by 100, and *Employment* is divided by 100. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw						
Dep. Var.	*I*(Rel.) × 100		Rel. (N. Loans) × 100		Rel. (A. Loan) × 100	
	(1)	(2)	(3)	(4)	(5)	(6)
I(African Ame.)	-0.76	-0.87	-0.91	-1.20	-0.04	-0.21
	(0.66)	(0.68)	(1.09)	(1.13)	(0.33)	(0.34)
I(Asian)	-0.72^{***}	-1.00^{***}	-1.09^{***}	-1.42^{***}	-0.06	-0.23^{**}
	(0.16)	(0.18)	(0.22)	(0.26)	(0.08)	(0.09)
I(Hispanic)	-1.11^{***}	-1.03^{***}	-1.60^{***}	-1.40^{***}	-0.25^{***}	-0.30^{***}
	(0.15)	(0.17)	(0.20)	(0.21)	(0.09)	(0.09)
Employment	2.34^{***}	2.11^{***}	3.56^{***}	3.21^{***}	2.99^{***}	2.96^{***}
	(0.43)	(0.45)	(0.59)	(0.61)	(0.32)	(0.34)
I(Franchise)	3.87^{***}	3.83^{***}	4.06^{***}	3.98^{***}	2.10^{***}	1.99^{***}
	(0.29)	(0.31)	(0.38)	(0.41)	(0.17)	(0.18)
City FEs		X		X		X
Business Type FEs	X	X	X	X	X	X
Observations	86,095	82,426	86,095	82,426	86,095	82,426
Adjusted R^2	0.011	0.008	0.009	0.004	0.011	-0.010
Panel B: 2021 PPP First Draw						
Dep. Var.	*I*(Rel.) × 100		Rel. (N. Loans) × 100		Rel. (A. Loan) × 100	
	(1)	(2)	(3)	(4)	(5)	(6)
I(African Ame.)	0.71	1.89	0.42	1.59	-0.24	-0.15
	(1.71)	(2.35)	(1.72)	(2.39)	(0.20)	(0.29)
I(Asian)	-0.47	-0.07	-0.70	-0.06	-0.23^{**}	-0.36^{*}
	(0.40)	(0.57)	(0.46)	(0.65)	(0.10)	(0.21)
I(Hispanic)	-0.69	-0.02	-0.90^{*}	0.02	-0.23	-0.15
	(0.45)	(0.67)	(0.52)	(0.79)	(0.16)	(0.22)
Employment	3.40	4.95	3.63	5.63	2.94^{**}	4.40^{**}
	(2.13)	(3.34)	(2.58)	(4.36)	(1.16)	(2.10)
I(Franchise)	1.43	1.61	1.75	2.27	0.35	0.60
	(0.99)	(1.25)	(1.23)	(1.67)	(0.34)	(0.49)
City FEs		X		X		X
Business Type FEs	X	X	X	X	X	X
Observations	6,022	3,984	6,022	3,984	6,022	3,984
Adjusted R^2	0.005	-0.011	0.004	-0.028	0.003	-0.095

Table 5 Fintech Lenders and Previous Lending Relationships

This table reports the linear probability regression results where the dependent variable is the *Fintech* loan indicator (0/1). The key independent variables are *I(Rel.)*, a dummy variable that equals 1 if the borrower had SBA 7(a) or 504 loans during 2009-2019, *Rel. (N. Loans)*, the total number of SBA 7(a) or 504 loans borrowed during 2009-2019, and *Rel. (A. Loans)*, the value (in USD millions) of SBA 7(a) or 504 loans borrowed during 2009-2019. In panels A and B, we report results on the 2020 and 2021 PPP waves, respectively. *A. Loan* is winsorized at the 1% and 99% cuts. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table A1. For demonstration purposes, the dependent variable is multiplied by 100. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: 2020 PPP First Draw						
Dep. Var.	*I*(Fintech) × 100					
	(1)	(2)	(3)	(4)	(5)	(6)
I(Rel.)	-5.76***	-5.31***				
	(0.48)	(0.53)				
Rel. (N. Loans)			-3.64***	-3.34***		
			(0.41)	(0.43)		
Rel. (A. Loan)					-4.60***	-4.96***
					(0.79)	(0.80)
Employment	-0.15***	-0.15***	-0.15***	-0.15***	-0.15***	-0.15***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
I(Franchise)	-1.14***	-1.10***	-1.22***	-1.17***	-1.28***	-1.22***
	(0.36)	(0.36)	(0.36)	(0.36)	(0.36)	(0.36)
City FEs		X		X		X
Business Type FEs	X	X	X	X	X	X
Observations	86,095	82,426	86,095	82,426	86,095	82,426
Adjusted R^2	0.035	0.058	0.035	0.058	0.034	0.057
Panel B: 2021 PPP First Draw						
Dep. Var.	*I*(Fintech) × 100					
	(1)	(2)	(3)	(4)	(5)	(6)
I(Rel.)	-15.60***	-10.38***				
	(0.81)	(1.97)				
Rel. (N. Loans)			-12.11***	-8.26***		
			(0.96)	(1.62)		
Rel. (A. Loan)					-16.66***	-11.31***
					(4.52)	(3.18)
Employment	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***
	(0.05)	(0.07)	(0.05)	(0.07)	(0.05)	(0.07)
I(Franchise)	-4.20**	-8.26***	-4.21**	-8.24***	-4.37**	-8.35***
	(1.89)	(2.81)	(1.90)	(2.82)	(1.89)	(2.80)
City FEs		X		X		X
Business Type FEs	X	X	X	X	X	X
Observations	6,022	3,984	6,022	3,984	6,022	3,984
Adjusted R^2	0.052	0.083	0.052	0.082	0.050	0.082

Table 6 Business Capital

This table reports the regression results from examining the impact of business capital on the difference in the minority-non-minority rating gap between fintech and non fintech lenders. The 2020 and 2021 waves are indicated in column heads. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. Business capital (*BC*) is proxied by the total number of ratings in the entire period of our analysis (from April 2018 to March 2021). *BC* is divided by 100 for demonstration purposes and winsorized at the 99% cuts. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample and control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. *Employment* is divided by 100 for demonstration purposes. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021.Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	**Rating Stars**							
Sample	2020 PPP First Draw				2021 PPP First Draw			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(FT) × BC	0.07	0.07*	0.03	0.03	0.00	-0.07	-0.00	0.04
	(0.04)	(0.04)	(0.13)	(0.11)	(0.09)	(0.12)	(0.09)	(0.12)
I(Asia.) × *I*(FT) × BC	0.11***	0.10***	0.08***	0.07***	0.24***	0.28***	0.12***	0.17***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.05)	(0.04)	(0.05)
I(Hisp.) × *I*(FT) × BC	0.13***	0.12***	0.09***	0.08***	0.06	-0.00	-0.08	-0.18
	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.09)	(0.08)	(0.11)
I(FT)	-0.02***	-0.01	-0.02	-0.01	-0.11***	-0.11**	-0.12***	-0.10*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.05)
I(African Ame.)	0.09***	0.13***	-0.00	0.01	0.11	0.25**	-0.08	-0.09
	(0.03)	(0.03)	(0.04)	(0.04)	(0.10)	(0.12)	(0.10)	(0.12)
I(Asian)	-0.11***	-0.10***	-0.05***	-0.05***	-0.17***	-0.16***	-0.06**	-0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)
I(Hispanic)	-0.10***	-0.10***	-0.12***	-0.11***	-0.11***	-0.06	-0.18***	-0.12**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.05)
Employment	-0.22***	-0.21***	-0.19***	-0.20***	-0.75***	-0.84***	-0.61***	-0.84***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.11)	(0.18)	(0.13)	(0.19)
I(Franchise)	-0.87***	-0.85***	-1.05***	-1.00***	-0.88***	-0.78***	-0.90***	-0.78***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.06)	(0.08)	(0.07)	(0.10)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	959,322	902,934	432,598	403,363	50,102	28,211	25,476	14,095
Adjusted R^2	0.044	0.064	0.049	0.069	0.041	0.053	0.040	0.048

Table 7 Relative Geographic Lending Scope

This table reports the regression results from examining the impact of geographic lending scope on the difference in the minority-non-minority rating gap between fintech and non fintech lenders. The 2020 and 2021 waves are indicated in column heads. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. Relative geographic lending scope (GS_r) is calculated as the total number of zip codes divided by the total number of cities that the lender covers in the entire PPP sample. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample and control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. *Employment* is divided by 100 for demonstration purposes. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. CDFIs and CDCs are excluded because their lending scope may be restricted to certain communities. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	Rating Stars							
Sample	2020 PPP First Draw				2021 PPP First Draw			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.)×I(FT)×GS_r	-0.07	-0.06	-0.15**	-0.15**	-0.07	-0.21	-0.07	-0.17
	(0.05)	(0.05)	(0.07)	(0.07)	(0.11)	(0.14)	(0.12)	(0.15)
I(Asian)×I(FT)×GS_r	-0.06***	-0.06***	-0.04***	-0.03**	0.02	0.06	-0.00	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
I(Hisp.)×I(FT)×GS_r	-0.00	0.01	-0.01	-0.00	0.05	0.06	-0.12**	-0.18**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.07)	(0.06)	(0.09)
I(FT)	0.05***	0.06***	0.05***	0.04***	-0.07*	-0.07	-0.06	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
I(African Ame.)	0.11***	0.14***	0.03	0.04	0.14	0.32**	-0.06	-0.02
	(0.03)	(0.03)	(0.04)	(0.04)	(0.11)	(0.13)	(0.12)	(0.14)
I(Asian)	-0.09***	-0.08***	-0.04***	-0.04***	-0.14***	-0.14***	-0.04	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.04)
I(Hispanic)	-0.09***	-0.09***	-0.11***	-0.11***	-0.12***	-0.08*	-0.15***	-0.09
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.05)	(0.04)	(0.06)
Employment	-0.21***	-0.21***	-0.19***	-0.19***	-0.71***	-0.83***	-0.60***	-0.81***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.11)	(0.18)	(0.13)	(0.19)
I(Franchise)	-0.88***	-0.86***	-1.05***	-1.00***	-0.88***	-0.77***	-0.90***	-0.77***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.06)	(0.08)	(0.07)	(0.10)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	952,731	896,408	429,480	400,262	49,403	27,632	25,036	13,745
Adjusted R^2	0.044	0.064	0.049	0.069	0.039	0.049	0.039	0.047

Table 8 First-Time Banks

This table reports the regression results of restaurants that borrow from lenders who are banks that participate in SBA programs for the first time and from lenders who had previously participated in SBA programs for the matched sample. We use the SBA 7(a) and 504 loan-level data from 1990-2019 to identify lenders that participated in SBA programs before. We exclude fintech lenders and non-banks. In Panel A, the dependent variable is the *New Bank* loan indicator (0/1) that equals one if the lender is a first-time bank in SBA programs. In Panel B, the dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. Other variable definitions, sample, the construction of the matched sample, and control variables are the same as in Table 2 (Panel A) and Table 3 (Panel B). Detailed variable definitions are in Appendix Table A1. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Standard errors are clustered at the city level (Panel A) and the restaurant level (Panel B), and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: First-Time Banks Usage Likelihood

Dep. Var.	*I*(New Bank) × 100							
	2020 PPP				2021 PPP			
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African Ame.)	-0.63	0.20	-0.54	0.44	5.31	7.54	5.13	7.36
	(0.92)	(0.93)	(0.94)	(0.96)	(6.32)	(7.76)	(6.43)	(7.87)
I(Asian)	-2.23***	-1.40***	-2.21***	-1.39***	-2.54***	-1.82**	-2.48***	-1.84**
	(0.21)	(0.21)	(0.21)	(0.21)	(0.71)	(0.79)	(0.71)	(0.83)
I(Hispanic)	-0.40	-0.12	-0.45*	-0.17	1.11	1.98	0.99	2.09
	(0.25)	(0.24)	(0.25)	(0.25)	(1.05)	(1.53)	(1.06)	(1.58)
Employment	-0.01***	-0.01***	-0.00	0.00	0.01	-0.01	0.03	-0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.04)	(0.04)
I(Franchise)	-0.42	-0.07	-0.35	-0.09	-1.13	0.77	-1.26	0.60
	(0.26)	(0.27)	(0.29)	(0.30)	(1.07)	(1.67)	(1.13)	(1.78)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	82,285	78,589	76,080	72,390	4,865	2,950	4,647	2,815
Adjusted R^2	0.002	0.132	0.002	0.133	0.005	0.098	0.004	0.094

Panel B: Rating Gap

Dep. Var.	**Rating Stars**							
Sample	2020 PPP				2021 PPP			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(New Bank)	-0.08	-0.07	0.09	0.05	0.66***	0.42*	0.41*	0.31
	(0.13)	(0.16)	(0.14)	(0.19)	(0.15)	(0.24)	(0.24)	(0.31)
I(Asian) × *I*(New Bank)	-0.05	-0.02	-0.02	-0.02	0.28*	0.18	-0.09	0.07
	(0.04)	(0.04)	(0.04)	(0.05)	(0.15)	(0.30)	(0.16)	(0.37)
I(Hisp.) × *I*(New Bank)	0.00	0.01	0.02	0.01	-0.09	-0.27	-0.28	-0.37
	(0.04)	(0.04)	(0.04)	(0.05)	(0.13)	(0.22)	(0.18)	(0.33)
I(New Bank)	0.04**	0.03	0.00	0.01	-0.04	0.13	0.22***	0.27*
	(0.01)	(0.02)	(0.02)	(0.02)	(0.08)	(0.17)	(0.07)	(0.14)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	845,747	789,355	380,498	351,392	38,183	19,342	19,275	9,592
Adjusted R^2	0.044	0.066	0.049	0.069	0.041	0.057	0.040	0.049

Table 9 Credit Unions

This table reports the regression results of restaurants that borrow from credit unions and from other lenders in the FFIEC list for the matched sample. We only include lenders that can be matched with THE FFIEC lender list. In panel A, the dependent variable is the *CU* loan indicator (0/1) that equals one if the lender is a credit union. In panel B, the dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. Other variable definitions, sample, the construction of the matched sample, and control variables are the same as in Table 2 (Panel A) and Table 3 (Panel B). Detailed variable definitions are in Appendix Table A1. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Standard errors are clustered at the city level (Panel A) and the restaurant level (Panel B), and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Credit Unions Usage Likelihood

Dep. Var.	*I*(CU) × 100							
	2020 PPP				2021 PPP			
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African Ame.)	1.87*	2.39**	1.90*	2.50**	6.48	7.42	6.10	7.09
	(1.02)	(1.02)	(1.05)	(1.04)	(5.75)	(6.55)	(5.70)	(6.57)
I(Asian)	-1.47***	-1.50***	-1.49***	-1.57***	-2.06***	-2.68***	-2.18***	-2.79***
	(0.17)	(0.21)	(0.17)	(0.21)	(0.71)	(0.87)	(0.72)	(0.90)
I(Hispanic)	0.15	0.51**	0.21	0.53**	-0.73	0.03	-0.87	0.28
	(0.27)	(0.25)	(0.27)	(0.26)	(0.94)	(1.34)	(0.94)	(1.35)
Employment	-0.02***	-0.02***	-0.03***	-0.03***	-0.03	-0.04	-0.08**	-0.13***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.03)	(0.03)	(0.05)
I(Franchise)	-1.09***	-0.83***	-1.08***	-0.80***	-1.22	1.28	-1.45	1.08
	(0.19)	(0.20)	(0.20)	(0.21)	(1.12)	(1.72)	(1.11)	(1.75)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	85,349	81,702	79,145	75,502	5,298	3,321	5,079	3,184
Adjusted R^2	0.004	0.099	0.004	0.098	0.004	0.069	0.008	0.083

Panel B: Rating Gap

Dep. Var.	**Rating Stars**							
Sample	2020 PPP				2021 PPP			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African Ame.)× *I*(CU)	-0.06	-0.07	-0.12	0.04	0.67***	0.54***	0.50**	0.70**
	(0.11)	(0.12)	(0.18)	(0.16)	(0.13)	(0.20)	(0.20)	(0.28)
I(Asian) × *I*(CU)	-0.04	-0.04	-0.12***	-0.11**	0.12	-0.12	0.00	0.17
	(0.04)	(0.04)	(0.04)	(0.05)	(0.11)	(0.17)	(0.13)	(0.24)
I(Hispanic) × *I*(CU)	-0.00	0.01	0.00	0.01	-0.11	-0.26	-0.01	0.29
	(0.04)	(0.04)	(0.04)	(0.05)	(0.15)	(0.18)	(0.15)	(0.27)
I(CU)	0.10***	0.10***	0.11***	0.11***	0.04	0.12	0.10	-0.18
	(0.01)	(0.02)	(0.02)	(0.02)	(0.06)	(0.10)	(0.07)	(0.14)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	882,486	826,845	396,912	368,112	41,716	21,715	20,931	10,694
Adjusted R^2	0.044	0.065	0.049	0.069	0.040	0.049	0.038	0.037

Table 10 CDFIs/CDCs

This table reports the regression results of restaurants that borrowed from community development oriented lenders and from banks for the matched sample. We exclude fintech lenders and other non-banks. In Panel A, the dependent variable is the *CDC* loan indicator (0/1) that equals one if the lender is a CDFI or CDC. In Panel B, the dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. Other variable definitions, sample, the construction of the matched sample, and control variables are the same as in Table 2 (Panel A) and Table 3 (Panel B). Detailed variable definitions are in Appendix Table A1. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Standard errors are clustered at the city level (Panel A) and the restaurant level (Panel B), and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: CDFIs/CDCs Usage Likelihood

Dep. Var.	*I*(CDC) × 100							
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African Ame.)	2.37***	2.27***	2.38***	2.33***	5.74	3.25	5.84	3.34
	(0.77)	(0.81)	(0.79)	(0.83)	(3.70)	(3.82)	(3.76)	(3.88)
I(Asian)	0.32***	0.15	0.29***	0.11	-0.50	-1.76**	-0.60	-2.07***
	(0.09)	(0.10)	(0.09)	(0.10)	(0.44)	(0.73)	(0.46)	(0.74)
I(Hispanic)	0.65***	0.53***	0.66***	0.55***	0.53	-0.74	0.41	-0.87
	(0.16)	(0.17)	(0.16)	(0.18)	(0.67)	(0.87)	(0.62)	(0.83)
Employment	-0.01***	-0.01***	-0.01***	-0.01***	-0.01	-0.02	-0.04**	-0.06*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.03)
I(Franchise)	-0.15**	-0.05	-0.14*	-0.04	-0.60	-2.53**	-0.44	-2.53**
	(0.07)	(0.08)	(0.08)	(0.08)	(0.83)	(1.22)	(0.88)	(1.07)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	82,819	79,121	76,603	72,910	4,961	3,033	4,740	2,890
Adjusted R^2	0.002	-0.013	0.002	-0.016	0.003	0.015	0.003	0.006

Panel B: Rating Gap

Dep. Var.	**Rating Stars**							
Sample	2020 PPP				2021 PPP			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri. Ame.)× *I*(CDC)	-0.05	-0.03	0.05	-0.01	0.06	-0.23	0.26	0.23
	(0.11)	(0.12)	(0.15)	(0.17)	(0.20)	(0.31)	(0.28)	(0.35)
I(Asian) × *I*(CDC)	-0.23***	-0.20***	-0.07	-0.09	0.09	0.15	-0.25	-0.18
	(0.07)	(0.07)	(0.08)	(0.09)	(0.11)	(0.21)	(0.19)	(0.28)
I(Hispanic) × *I*(CDC)	-0.06	0.04	0.05	0.11	0.01	0.06	-0.03	0.45
	(0.07)	(0.08)	(0.09)	(0.10)	(0.15)	(0.31)	(0.20)	(0.28)
I(CDC)	0.20***	0.16***	0.07	0.04	0.09	0.11	0.12	0.03
	(0.04)	(0.04)	(0.05)	(0.06)	(0.09)	(0.13)	(0.08)	(0.12)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	852,090	795,599	383,485	354,350	38,882	19,848	19,715	9,915
Adjusted R^2	0.044	0.065	0.048	0.069	0.041	0.058	0.039	0.049

Table 11 Approval Date

This table reports the regression results from examining the difference in PPP loan approval dates between minority- and non-minority-owned restaurants that borrow from fintech and non-fintech lenders. The dependent variable, *Δ(Approval Date-PPP Starting Date)*, is the difference between PPP loan approval date and PPP starting date. The starting date is April 03, 2020 for the 2020 wave and Jan 12, 2021 for the 2021 wave. The 2020 and 2021 waves are indicated in column heads. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	Δ(Approval Date-PPP Starting Date)							
Sample	2020 PPP First Draw				2021 PPP First Draw			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(Fintech)	-3.30	-2.20	-3.12	-2.01	-3.61	-0.01	-3.82	-0.04
	(3.10)	(3.25)	(3.10)	(3.26)	(4.13)	(4.65)	(4.14)	(4.69)
I(Asian) × *I*(Fintech)	2.23^{***}	3.11^{***}	2.52^{***}	3.39^{***}	-8.11^{***}	-7.34^{***}	-8.20^{***}	-7.54^{***}
	(0.74)	(0.76)	(0.74)	(0.77)	(1.57)	(2.16)	(1.58)	(2.17)
I(Hispanic) × *I*(Fintech)	0.80	0.06	0.83	0.11	-8.72^{***}	-6.71^{**}	-8.75^{***}	-6.83^{**}
	(1.12)	(1.15)	(1.11)	(1.15)	(2.04)	(2.64)	(2.06)	(2.68)
I(Fintech)	14.31^{***}	11.93^{***}	13.63^{***}	11.27^{***}	2.42^{**}	0.66	2.38^{**}	0.50
	(0.47)	(0.52)	(0.48)	(0.52)	(0.94)	(1.28)	(0.96)	(1.30)
I(African Ame.)	9.63^{***}	7.61^{***}	8.88^{***}	6.86^{***}	8.71^{***}	4.35	8.91^{***}	4.56
	(1.23)	(1.29)	(1.24)	(1.29)	(2.65)	(2.98)	(2.72)	(3.06)
I(Asian)	10.37^{***}	9.08^{***}	9.72^{***}	8.47^{***}	2.43^{***}	1.42	2.29^{***}	1.28
	(0.32)	(0.33)	(0.31)	(0.33)	(0.77)	(1.09)	(0.78)	(1.10)
I(Hispanic)	5.47^{***}	4.98^{***}	5.30^{***}	4.84^{***}	3.15^{***}	2.51^{*}	3.18^{***}	2.50^{*}
	(0.28)	(0.28)	(0.28)	(0.29)	(0.89)	(1.30)	(0.90)	(1.33)
Employment	-0.09^{***}	-0.09^{***}	-0.20^{***}	-0.19^{***}	-0.05^{**}	-0.05	-0.12^{***}	-0.14^{***}
	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)
I(Franchise)	-8.15^{***}	-7.91^{***}	-7.93^{***}	-7.89^{***}	1.21	0.92	1.62	1.84
	(0.20)	(0.21)	(0.22)	(0.23)	(1.14)	(1.59)	(1.19)	(1.61)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	92,556	88,873	86,095	82,426	6,266	4,150	6,022	3,984
Adjusted R^2	0.140	0.176	0.142	0.176	0.030	0.036	0.019	0.025

Table 12 Restaurant Ratings (Robustness –Approval Date Fixed Effects)

This table reports the robustness check results of Table 3 which examine the difference in ratings between minority- and non-minority-owned restaurants that borrow from fintech and non-fintech lenders. We add approval date fixed effects as control variables. Other than that, the specifications are the same as in Table 3. In Panels A and B, we report results on the 2020 and 2021 PPP waves, respectively. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample and other control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw								
Dep. Var.	**Rating Stars**							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afr.) × *I*(Fintech)	-0.11	-0.09	-0.11	-0.08	-0.25**	-0.23**	-0.25**	-0.23**
	(0.08)	(0.08)	(0.08)	(0.08)	(0.11)	(0.11)	(0.11)	(0.11)
I(Asian) × *I*(Fintech)	-0.08***	-0.08***	-0.08***	-0.08***	-0.06***	-0.04	-0.06***	-0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
I(Hispanic) × *I*(Fintech)	-0.01	0.01	-0.01	0.01	-0.01	0.01	-0.02	-0.00
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
I(Fintech)	0.06***	0.06***	0.06***	0.06***	0.05***	0.04**	0.05***	0.04**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	1032002	974781	959322	902934	464638	434947	432597	403362
Adjusted R^2	0.047	0.068	0.044	0.065	0.052	0.073	0.049	0.069
Panel B: 2021 PPP First Draw								
Dep. Var.	**Rating Stars**							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afr.) × *I*(Fintech)	-0.12	-0.32	-0.13	-0.35	-0.10	-0.25	-0.10	-0.27
	(0.17)	(0.21)	(0.16)	(0.21)	(0.18)	(0.21)	(0.18)	(0.22)
I(Asian) × *I*(Fintech)	0.01	0.08	0.01	0.09	-0.02	0.02	-0.01	0.05
	(0.06)	(0.09)	(0.06)	(0.09)	(0.07)	(0.10)	(0.07)	(0.10)
I(Hispanic) × *I*(Fintech)	0.07	0.11	0.07	0.10	-0.17**	-0.28**	-0.17**	-0.28**
	(0.07)	(0.11)	(0.07)	(0.11)	(0.09)	(0.13)	(0.09)	(0.13)
I(Fintech)	-0.07*	-0.07	-0.08*	-0.09	-0.07	-0.01	-0.07*	-0.02
	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.07)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	51844	29256	50102	28211	26491	14721	25476	14093
Adjusted R^2	0.042	0.054	0.042	0.056	0.043	0.057	0.042	0.054

Appendix

Table A1 Variable Definition

Variable Name	Definition	Data Source
I(Fintech)	1 if the lender of the loan is a fintech lender, 0 otherwise	• PPP loan-level dataset • Consolidated fintech company list
I(Minority) I(African Ame.) I(Asian) I(Hispanic)	1 if the restaurant is of minority food type, 0 otherwise 1 if the restaurant is of African American food type, 0 otherwise 1 if the restaurant is of Asian food type (including Pacific Islander), 0 otherwise 1 if the restaurant is of Hispanic food type, 0 otherwise *When multiple food categories, African American ≳ Asian ≳ Hispanic.*	• yelp.com • Food type classification list
Rating Stars Eating Policy Food Price BC	Mean of all the customer ratings in the month which range from 0 to 5 Dummies for the following restaurant amenities: delivery, takeout, reservations, and outdoor seating Dummies for $,$$,$$$,$$$$ Business capital: the total number of ratings in the entire period of our analysis (from April 2018 to March 2021)	• yelp.com
Δ(Approval Date-PPP Starting Date) Employment I(Franchise) Business Type FEs Approval Date FEs GS_{zip} GS_{city}	Number of days between the date approved and April 3rd, 2020 for the 2020 PPP number of days between the date approved and Jan 12th, 2021 for the 2021 PPP *Jobs Reported* in the SBA original dataset 1 if the *Franchise Name* in the SBA original dataset is non-empty after our adjustments (see Online Appendix C3) Dummies based Business yype in the SBA original dataset, including the types of : Cooperative Corporation, Employee Stock Ownership Plan(ESOP), Independent Contractors, Joint Venture, Limited Liability Company(LLC), Limited Liability Partnership, Partnership, Professional Association, Qualified Joint-Venture (spouses), Self-Employed Individuals, Single Member LLC, Sole Proprietorship, Subchapter S Corporation, Tenant in Common, Tribal Concerns, Trust Dummies for the approval date in the SBA original dataset the total number of zip codes that the lender covers in the entire PPP loan sample The total number of cities that the lender covers in the entire PPP loan sample	• PPP loan-level dataset
City FEs	Dummies for cities Convert zip code in the SBA original dataset to city using the HUD-USPS ZIP Code Crosswalk data. If the zip code-city conversion is not available in the HUD data, we manually searched and find the city in the format in the HUD data. *We do not directly use the city information in the PPP data due to quality concerns.*	• PPP loan-level dataset • HUD User
New Bank	1 if the lender is a first-time bank, 0 otherwise (fintech lenders and non-banks are excluded) To identify whether the bank previously participated in the SBA programs, we use a combination of code-based and manual checks of lender name matching with the SBA 7(a) and 504 loan-level data from 1990-2019.	• PPP loan-level dataset • SBA 7(a) and 504 loan-level dataset (1990-2019)

Table A1 Variable Definition (Cont.)

CD	1 if the lender is a CDFI or CDC, 0 otherwise (fintech lenders and other non-banks are excluded)	• cdfifund.gov • SBA 504 (1990-2019)
Uninsured S&L CU	1 if the lender is not federally insured, 0 otherwise 1 if the lender is a Savings & Loan Association, 0 otherwise 1 if the lender is a Credit Union, 0 otherwise	• FFEIC *Missing if not matched with FFEIC*
I(Rel.) Rel. (N. Loans) Rel. (A. Loan)	1 if the borrower previously borrowed a SBA 7(a) or 504 loan Total number of SBA 7(a) and 504 loans the borrower has Total dollar value of SBA 7(a) and 504 loans the borrower has (million USD)	SBA 7(a) and 504 loan-level dataset (2009-2019)

Table A2 The List of Fintech Lenders in the First Draw of the PPP Program

Pair #	Servicing Lender	Originating Lender	N. Our	Our/722	N. 722	N. All
1	Cross River Bank	Cross River Bank	2165	26%	8440	324588
2	Cross River Bank Kabbage, Inc.	Kabbage, Inc.	1828	23%	7859	159823
3	Square Capital, LLC	Square Capital, LLC Celtic Bank Corporation	1521	22%	6966	86109
4	WebBank	WebBank	1415	31%	4639	82997
5	First Home Bank Loan Source Incorporated	Loan Source Incorporated some bank[36]	1019	28%	3654	36515
6	Itria Ventures LLC	Itria Ventures LLC	499	4%	12106	197238
7	Customers Bank Readycap Lending, LLC	Readycap Lending, LLC	413	13%	3301	67836
8	FC Marketplace, LLC (dba Funding Circle) Quontic Bank	FC Marketplace, LLC (dba Funding Circle)	187	25%	747	9738
9	Celtic Bank Corporation	Celtic Bank Corporation	155	30%	521	65376
10	Fundbox, Inc.	Fundbox, Inc.	119	23%	511	13454
11	Sunrise Banks, National Association	Sunrise Banks, National Association	69	32%	216	2200
12	BSD Capital, LLC dba Lendistry	BSD Capital, LLC dba Lendistry	67	23%	295	4814
13	Intuit Financing Inc. Quontic Bank	Intuit Financing Inc.	48	33%	145	17792
14	Opportunity Fund Community Development	Opportunity Fund Community Development	16	24%	67	1162
15	FinWise Bank	FinWise Bank	16	35%	46	693

[36] Loan Source shown in the PPP loan-level dataset to have the following 37 originators in the 2020-PPP round: Columbia Community CU, First State Bank, Renaissance Community Loan Fund, Inc., The Bryn Mawr Trust Company, Neighbors FCU, Ascend FCU, FirstBank, BNC National Bank, Pelican State CU, First Reliance Bank, Nano Banc, Pacific Premier Bank, Signature Bank of Georgia, The Hicksville Bank, Florida Capital Bank, National Association, Flagstar Bank, FSB, First Bank of Alabama, Stearns Bank National Association, Sterling National Bank, Bethpage FCU, Marlin Business Bank, KeyPoint CU, BCB Community Bank, Kearny Bank, Five Star Bank, Community Bank and Trust Company, Investors Bank, Peapack-Gladstone Bank, OceanFirst Bank, National Association, Financial Partners CU, Prudential Bank, Gather FCU, Northeast Bank, Southern First Bank, Malvern Bank, National Association, Orange County's CU, Neighborhood National Bank.

A Short Description on the Paycheck Protection Program

The Paycheck Protection Program (PPP) is a Small Business Administration (SBA) loan program established on April 3, 2020 as a temporary addition to the existing 7(a) loan program, in accordance with the Coronavirus Aid, Relief, and Economic Security Act (CARES Act) passed on March 27, 2020. The intent of the PPP is to provide small businesses with funds to maintain payroll costs and cover overheads during the Covid-19 crisis.

The first tranche of the 2020 PPP loans started on April 3, 2020. Until April 16, 2020, the initial allocation of $349 billion authorized by Congress was exhausted. The distribution of the second tranche of the PPP started on April 27 after Congress added additional funding to the program. The initial application deadline for the PPP loans was June 30, 2020 and later extended to August 8, 2020. As of August 8, 2020, in total $525 billion PPP loans were distributed, and $134 billion remained available. In total, $659 billion funds were authorized to the PPP by Public Law 116-147 in 2020.

The Economic Aid to Hard-Hit Small Businesses, Nonprofits, and Venues Act (Economic Aid Act) restarted the issuance of PPP loans in January 2021. The Act added $284 billion funding for PPP loans. The initial deadline of applying for PPP loans is March 31, 2021, later extended to May 31. The 2021 PPP program consists of a first draw for whom have not received a PPP loan before and a second draw for previous PPP recipients in 2020. Moreover, in 2021, the SBA undertook several steps to facilitate lending to minority borrowers, including encourage minority owned lenders to become PPP lenders.

For most industries, the eligibility requirement is either meeting the SBA size standards for small business or less than 500 employees. For the industries with a NAICS code that begins with 72 (Accommodations and Food Services), the business is eligible for the PPP as long as the number of employees is fewer than 500 at each location.

The PPP loans should generally be used for payroll costs and for mortgage interest, rent, utilities, and other worker protection related cost and the interest rate is fixed at 1%. The maturity of the loans issued before June 5, 2020 is two years and five years for loans issued after June 5. The principal of the PPP loan can be partially or fully forgiven conditioning on the loan spending on business maintaining and employee rehiring and maintaining. There is no collateral or personal guarantees requirement. Each loan is 100% guaranteed by the SBA.

Fintech played a crucial role in the distribution of PPP loans. Because of the large amount of loan demand, the goal of providing immediate assistance to borrowers, and the social-distancing requirement during the pandemic, the SBA allowed for a few non-traditional lenders specializing in fintech services to become eligible lenders, in addition to the SBA 7(a) lender, federally insured depository institution or credit union. Examples of fintech lenders in the PPP are Lendio, Paypal, Biz2credit, Kabbage, and Square.

This is the first large scale experiment of including fintech lenders in SBA programs. Most of the fintech companies are not participants in the SBA 7(a) or 504 programs before the Covid-19 crisis and therefore not PPP eligible lenders by default. At the very early stage of the PPP program in 2020, non-depository institutions including fintech companies were not able to operate similarly to depository institutions. On April 8, five days after the beginning of issuing PPP loans, the Federal Reserve Board authorized each regional Federal Reserve Banks to establish the Paycheck Protection Program Liquidity Facility (PPPLP), to provide liquidity to credit market by extending non-recourse credit to PPP lenders and taking PPP loans as collateral. The PPPLF became fully functional on April 16, but only eligible to depository institutions. On April 30, the PPPLP was extended to all PPP lenders approved by the SBA, including fintech companies.

Compare the Racial Group Measures PPP vs Yelp.com

Table A3 The List of Fintech Lenders in the First Draw of the PPP Program

This table reports the relationship between the racial group classification using information from PPP data and Yelp data. Panel A reports the share of each racial group based on information in the PPP loan-level data for each racial group using food type information from yelp.com. Rows indicate the racial group of the restaurant owners in the PPP dataset. Columns indicate the racial group of the restaurant using food type information from yelp.com. For example, the first row of the third column reports that 26.9% of restaurants that are classified as Hispanic based on information from yelp.com are classified as White based on PPP information. Panel B reports the parallel results of shares of Yelp racial groups for each PPP racial groups. Panel C reports the pairwise correlations between PPP race classifications and yelp race classifications. The sample includes all restaurant borrowers which have a valid yelp link and non-missing race and ethnicity information in the PPP dataset.

Panel A: Cross Shares – Compare Yelp with PPP

	Yelp				
PPP	White	Non-White	Hispanic	African Ame.	Asian
White	74.9%	12.2%	26.9%	12.0%	4.7%
Non-White	25.1%	87.8%	73.1%	88.0%	95.3%
Hispanic	3.9%	18.3%	51.9%	1.8%	1.8%
African Ame.	4.0%	5.2%	7.5%	80.1%	0.5%
Asian	13.7%	59.5%	5.9%	1.8%	89.6%
Native Ame.	3.5%	4.8%	7.8%	4.2%	3.4%
Observations	13,327	5,498	1,806	166	3,526

Panel B: Cross Shares – Compare PPP with Yelp

	PPP					
Yelp	White	Non-White	Hispanic	African Ame.	Asian	Native Ame.
White	93.7%	40.9%	34.2%	65.0%	35.8%	63.6%
Non-White	6.3%	59.1%	65.8%	35.0%	64.2%	36.4%
Hispanic	4.6%	16.2%	61.5%	16.4%	2.1%	19.3%
African Ame.	0.2%	1.8%	0.2%	16.2%	0.1%	1.0%
Asian	1.6%	41.1%	4.1%	2.3%	62.0%	16.2%
Observations	10,657	8,168	1,525	821	5,092	730

Panel C: Pairwise Correlation

	(1) Minority Yelp	(2) African Yelp	(3) Asian Yelp	(4) Hispanic Yelp
Minority PPP	0.58^{***}			
	(0.00)			
African PPP		0.35^{***}		
		(0.00)		
Asian PPP			0.52^{***}	
			(0.00)	
Hispanic PPP				0.68^{***}
				(0.00)
Observations	18,825			

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Proof of Proposition 1

Setting the outside option of borrowers to zero, the equilibrium in the race-biased tech-preference case is given by $(\underline{\gamma_{mf}}, \underline{\gamma_{mb}}, \underline{\gamma_{nf}}, \underline{\gamma_{nb}}, p_{mf}, p_{mb}, p_{nf}, p_{nb})$ that are determined by

$$M^m \int_{\underline{\gamma_{mf}}}^{\infty} f(x, \mu^m, \sigma^m)dx + M^n \int_{\underline{\gamma_{nf}}}^{\infty} f(x, \mu^n, \sigma^n)dx = M^f \quad (A.1)$$

$$M^m \int_{\underline{\gamma_{mb}}}^{\underline{\gamma_{mf}}} f(x, \mu^m, \sigma^m)dx + M^n \int_{\underline{\gamma_{nb}}}^{\underline{\gamma_{nf}}} f(x, \mu^n, \sigma^n)dx = M^b \quad (A.2)$$

$$\underline{\gamma_{mf}}(1 + \theta^m) - p_{mf} = \underline{\gamma_{mf}} - p_{mb} \quad (A.3)$$

$$\underline{\gamma_{nf}}(1 + \theta^n) - p_{nf} = \underline{\gamma_{nf}} - p_{nb} \quad (A.4)$$

$$\underline{\gamma_{mb}} - p_{mb} = 0 \quad (A.5)$$

$$\underline{\gamma_{nb}} - p_{nb} = 0 \quad (A.6)$$

$$p_{mf} = p_{nf} \quad (A.7)$$

$$p_{mb} = p_{nb} \quad (A.8)$$

$(A.3)$ to $(A.6)$ are the incentive compatibility constraints for the marginal borrower in the minority-fintech, non-minority-fintech, minority-bank, and non-minority-bank matches respectively.

$(A.7)$ and $(A.8)$ are the lender's incentive compatibility.

$$(A.5) + (A.6) + (A.8) \Rightarrow \underline{\gamma_{mb}} = \underline{\gamma_{nb}} \quad (A.9)$$

$$(A.3) + (A.4) + (A.7) \Rightarrow \underline{\gamma_{mf}}\theta^m = \underline{\gamma_{nf}}\theta^n \quad (A.10)$$

■

Proof of Corollary 1

The minority-non-minority rating gap in matching thresholds between fintech lenders and banks is,

$$(A.9) + (A.10) \Rightarrow \underline{\Delta\Delta} \stackrel{\text{def}}{=} \left(\underline{\gamma_{mf}} - \underline{\gamma_{nf}}\right) - \left(\underline{\gamma_{mb}} - \underline{\gamma_{nb}}\right) = \underline{\gamma_{mf}} - \underline{\gamma_{nf}}$$

$$= \frac{\underline{\gamma_{mf}}}{\theta^n}(\theta^n - \theta^m) < 0 \; if \; \theta^m > \theta^n$$

In addition, minority-non-minority gap in the conditional expectation of the rating level between fintech lenders and banks is,

$$\mathbb{E}(\Delta\Delta|\cdot) \stackrel{\text{def}}{=} \left[\mathbb{E}\left(x \middle| x \geq \underline{\gamma_{mf}}, \mu^m, \sigma^m\right) - \mathbb{E}\left(x \middle| x \geq \underline{\gamma_{nf}}, \mu^n, \sigma^n\right)\right] - \left[\mathbb{E}\left(x \middle| \underline{\gamma_{mb}} \leq x < \underline{\gamma_{mf}}, \mu^m, \sigma^m\right) - \mathbb{E}\left(x \middle| \underline{\gamma_{nb}} \leq x < \underline{\gamma_{nf}}, \mu^n, \sigma^n\right)\right]$$

$$= \left[\mu^m + \sigma^m \frac{\varphi(\frac{\underline{\gamma_{mf}} - \mu^m}{\sigma^m})}{1 - \Phi(\frac{\underline{\gamma_{mf}} - \mu^m}{\sigma^m})} - \sigma^n \frac{\varphi\left(\frac{\underline{\gamma_{nf}} - \mu^n}{\sigma^n}\right)}{1 - \Phi(\frac{\underline{\gamma_{nf}} - \mu^n}{\sigma^n})}) - \mu^n\right] - \left[\mu^m + \sigma^m \frac{\varphi\left(\frac{\underline{\gamma_{mb}} - \mu^m}{\sigma^m}\right) - \sigma^m \varphi\left(\frac{\underline{\gamma_{mf}} - \mu^m}{\sigma^m}\right)}{\Phi\left(\frac{\underline{\gamma_{mf}} - \mu^m}{\sigma^m}\right) - \Phi\left(\frac{\underline{\gamma_{mb}} - \mu^m}{\sigma^m}\right)} - \sigma^n \frac{\varphi\left(\frac{\underline{\gamma_{nb}} - \mu^n}{\sigma^n}\right) - \varphi\left(\frac{\underline{\gamma_{nf}} - \mu^n}{\sigma^n}\right)}{\Phi\left(\frac{\underline{\gamma_{nf}} - \mu^n}{\sigma^n}\right) - \Phi\left(\frac{\underline{\gamma_{nb}} - \mu^n}{\sigma^n}\right)} - \mu^n\right]$$

$$= \sigma^m \left[\frac{\varphi(\frac{\underline{\gamma_{mf}} - \mu^m}{\sigma^m})}{1 - \Phi(\frac{\underline{\gamma_{mf}} - \mu^m}{\sigma^m})} - \frac{\varphi\left(\frac{\underline{\gamma_{mb}} - \mu^m}{\sigma^m}\right) - \varphi\left(\frac{\underline{\gamma_{mf}} - \mu^m}{\sigma^m}\right)}{\Phi\left(\frac{\underline{\gamma_{mf}} - \mu^m}{\sigma^m}\right) - \Phi\left(\frac{\underline{\gamma_{mb}} - \mu^m}{\sigma^m}\right)}\right] - \sigma^n \left[\frac{\varphi\left(\frac{\underline{\gamma_{nf}} - \mu^n}{\sigma^n}\right)}{1 - \Phi(\frac{\underline{\gamma_{nf}} - \mu^n}{\sigma^n})} - \frac{\varphi\left(\frac{\underline{\gamma_{nb}} - \mu^n}{\sigma^n}\right) - \varphi\left(\frac{\underline{\gamma_{nf}} - \mu^n}{\sigma^n}\right)}{\Phi\left(\frac{\underline{\gamma_{nf}} - \mu^n}{\sigma^n}\right) - \Phi\left(\frac{\underline{\gamma_{nb}} - \mu^n}{\sigma^n}\right)}\right] \text{(A.11)}$$

Where $\varphi(\cdot)$ and $\Phi(\cdot)$ are the density and cumulative distribution function of the standard normal distribution respectively.

Suppose that the underlying distribution is the same for minority and non-minority borrowers, i.e., $\mu^m = \mu^n = \mu$ and $\sigma^m = \sigma^n = \sigma$, combined with $(A.9)$ $\underline{\gamma_{mb}} = \underline{\gamma_{nb}} = \sigma\tilde{\gamma} + \mu$, (A.11) becomes,

$\sigma\left(G\left(\frac{\underline{\gamma_{mf}} - \mu}{\sigma}\right) - G\left(\frac{\underline{\gamma_{nf}} - \mu}{\sigma}\right)\right)$, where $G(x) = \frac{\varphi(x)}{1 - \Phi(x)} - \frac{\varphi(\tilde{\gamma}) - \varphi(x)}{\Phi(x) - \Phi(\tilde{\gamma})}$.

Using the symmetricity of normal distribution, $G(x) = \frac{\varphi(x)}{1 - \Phi(x)} - \frac{\varphi(\tilde{\gamma}) - \varphi(x)}{\Phi(x) - \Phi(\tilde{\gamma})} = \frac{\varphi(x)}{\Phi(-x)} + \frac{\varphi(x) - \varphi(\tilde{\gamma})}{\Phi(x) - \Phi(\tilde{\gamma})}$

■